# DEMAND RESPONSE IN THE DOMESTIC ENVIRONMENT

An assessment of the potential of domestic heat pumps to provide ancillary services on the Dutch FCR market

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# Table of contents

# Acknowledgements

Any master thesis research includes ups and downs, leading in the end to satisfaction. This project was no exception. Multiple setbacks have almost led to the decision to abort the project. However, my intrinsic motivation and interest for the topic kept me from doing so, a decision that I do not regret. I learned a lot about the balancing system, the electricity markets and what it is like to work at a tech-startup in this sector. Building a model in Python like the one in this research with only very limited programming experience prior to this project was challenging. However, it rewarded me with skills as a data scientist that will prove its value in my future career. I am convinced that demand response is going to play a major role in future energy systems and that knowledge about this topic and about the balancing system of the electricity grid is of great value for anyone who plans a career in the (sustainable) energy sector.

I could not have successfully finished this project without the support of family, friends, colleagues and my supervisors. I want to thank my supervisors at the University, Ioannis Lampropoulos and Wouter Schram, for keeping me focused by being critical, while at the same time being supportive when needed. In addition, I am thankful to my colleagues at Sympower, especially my supervisors Simon Bushell and Laura van Jaarsveld for supervising me, providing insights in the balancing markets and supporting me with the process of learning to write code. Finally, I want to thank my family for their support and for helping with making decisions. Special gratitude goes to my father and to my brother in law (Pieter Wijne) who allowed me to use their desktop computers to run the model in the final weeks of my research. I wish to anyone who reads this report that their knowledge and understanding about the balancing system is expanded.

# Executive summary

Due to the transition towards a low-carbon energy system, more renewable energy resources are being integrated into the energy mix. The intermittent nature of these resources makes balancing electricity supply and demand more challenging. One technique that can contribute to balancing supply and demand is demand response (DR), in which final consumers provide flexibility to the electricity system by voluntarily changing their usual electricity consumption in response to system frequency. An example of an appliance that can be used as DR-asset is the domestic heat pump. Domestic heat pumps can be aggregated into a portfolio that delivers flexibility by a so called DR-aggregator, an organization that enables small electricity consumers to offer flexibility by bundling them into a portfolio. Flexibility can be offered on different markets, amongst others the Frequency Containment Reserve (FCR) market, in which a DR-aggregator can offer bidirectional flexibility (increase or reduce demand) on a weekly basis. The aggregator can settle a weekly bid at a chosen capacity, from which they are expected to deliver that capacity during the week, as a response to frequency fluctuations. The performance of the aggregator is expressed in terms of reliability and availability. Not being reliable leads to fines for Inadequate Response, whereas not having sufficient flexible capacity available leads to fines for Non-Availability.

This research aims to investigate the potential for an aggregated portfolio of domestic heat pumps to deliver flexibility on the FCR market. To achieve this, a quantitative model is built in Python that combines historical frequency data with heat pump data from 22 weeks to simulate a switching and bidding process. The potential for FCR is quantitatively expressed in terms of bid size and net revenue.

Three strategies are considered that the aggregator can apply to determine the weekly bid size. Firstly, by applying a reliable strategy, the aggregator aims to choose the bid size in such a way that it can always provide 100% reliability and availability. Secondly, with the optimization strategy, the aggregator aims for a bid size at which the fines are at an acceptable level and net revenue is maximized. Finally, with the opportunistic strategy, the aggregator is able to avoid fines for non-availability by either misinforming the TSO about the portfolio capacity, or having a back-up portfolio that is not switched, but available for capacity. The aggregator then selects the bid size based on an acceptable level of fines for Inadequate Response.

Results show that the net revenue that the aggregator can generate per household at current market conditions is relatively low, making a project in which heat pumps deliver FCR with the methods described in this research financially challenging. The net revenue can be increased by selecting households with high-capacity heat pumps and combining heat pumps in a portfolio with other assets. Implementation barriers and operational costs for the aggregator are considered out of scope of this project, but might evolve over time and change the feasibility of the project. In addition, non-availability fines seem to be a stronger limiting factor to the potential for FCR compared to fines for inadequate response. This leads to a large difference in potential between the three strategies. Net-revenue optimization methods used in the opportunistic and optimization strategy might jeopardize the integrity towards the party that procures flexibility and should therefore, if applied, be used with caution. Other factors that are found to influence the results are market developments, TSO regulations and comfort constraints of end-users.

# List of abbreviations

| Acronym | Full words | Description |
|---|---|---|
| AFP | Available Flexible Power | The available flexibility in the portfolio at a given moment |
| BRP | Balance Responsible Party | Organization that bears the responsibility of balancing supply and demand for its portfolio of consumers |
| CWE | Central Western Europe | - |
| DF | Dataframe | Type of data collection used in data science |
| DR | Demand response | The process through which final consumers provide flexibility to the electricity system by voluntarily changing their usual electricity consumption |
| DLC | Direct Load Control | The process of directly altering the power consumption of an electrical device |
| ENTSO-E | European Network For Transmission System Operators | Joint cooperation of TSO's through Europe |
| FCR | Frequency Containment Reserve | Flexibility market for short term frequency deviations. Also known as primary reserve market |
| IR | Inadequate Response | The event where the aggregator was not able to respond correctly to a frequency deviation. Such an event results in IR-fines |
| NA | Non-Availability | The event where the power consumption of the portfolio is insufficient given the bid capacity, not reliable on frequency. Such an event results in NA-fines |
| RFP | Required Flexible Power | The required capacity with which the power should be switched at a given moment |
| TSO | Transmission system operator | System operator that is responsible for the High-voltage electricity grid and the balancing system. In the Netherlands, this is TenneT |

# 1 Introduction

This chapter starts with introducing demand response, aggregators and the FCR market, after which the research question and sub questions are formulated. Then, a short introduction to the methodology is provided, as well as a reading guide for the report.

## 1.1 Problem statement

Given the transition towards a low-carbon energy supply system, the share of electricity produced by renewable energy resources is likely to increase. In Europe, wind and solar energy have the highest potential in terms of renewable electricity generation. Both wind and solar energy resources are intermittent, since their production strongly depends on weather patterns (Weitemeyer et al., 2015). To maintain the system frequency within acceptable limits, electricity supply and demand need to be balanced. Traditionally, supply could be altered to match demand by dispatching generators, powered by fossil fuels. Given the shift towards renewable energy production, alternative methods to provide these grid balancing services need to be found. One of these methods is Demand Response (DR), also known as demand side management (Aghaei &Alizadeh, 2013). DR is defined by Eurelectric (2015) as "The process through which final consumers (households or businesses) provide flexibility to the electricity system by voluntarily changing their usual electricity consumption in reaction to price signals or to specific requests, while at the same time benefiting from doing so" (p.3).

For small consumers to use their flexible load for financial or balancing purposes, a new role is needed in the energy value chain; the role of DR aggregators. A DR-aggregator is defined by Wang et al. (2015) as "an intermediary between small consumers and other players (e.g., the retailers, or distribution companies) in the system". Aggregators bundle the flexibility of individual consumers or businesses into a portfolio of devices that can be either be switched on or off, depending on the needs for stabilising the grid. By doing so, aggregators can enable smaller units (consumers or businesses) to participate indirectly on the flexibility market and get financial benefits in return. An example of a method that can be used to achieve this is Direct Load Control (DLC), in which the aggregator is allowed to directly control a set of appliances in the end-user premises. (Paterakis et. Al, 2017).

In the Netherlands, short term frequency deviations can be balanced through the Frequency Containment Reserve (FCR) market, also known as primary reserve (TenneT, 2017). In the FCR market, a bidding system is applied in which parties offer a certain amount of flexible power, that they have to deliver whenever necessary. In return, they receive a financial compensation from the Transmission System Operator (TSO) for the capacity for which they are available. Any bid that is offered by an aggregator to the TSO has to meet certain requirements according to the regulations in place that are specified by the TSO (TenneT, 2017). As with most regulations, not meeting the promised bids results in a fine, which the DR-aggregator has to pay to the TSO. Two types of fines are enforced on the FCR-market, fines for non-availability (NA-fines) and fines for inadequate response (IR-fines).

In order to comply with the FCR-requirements, DR-aggregators need to choose their portfolio of DR assets in such a way that it can deliver the promised amount of flexibility, thereby meeting the prerequisites of the FCR market. With a given portfolio, aggregators can choose how much they are willing to bid during the next bidding period. Determining the bid size for each bid period is a strategic process. If the aggregator bids too low, revenue and thus profit can be suboptimal. On the other hand, if the aggregator bids too high, the aggregator might not be able to deliver the bid flexibility and therefore risks fines. The length of the bidding period is country- and market specific. When the bid size is determined, the aggregator is bound to deliver that amount of flexibility during the complete bidding period, as response to frequency deviations (TenneT, 2017).

## 1.2 Research questions

Many different technologies exist that have potential to operate as DR-asset, both in the residential and industrial sector, for example the domestic heat pump. Heat pumps convert electrical power into heat that can be used for heating households and supplying hot tap water (Stadler, 2008). Heat pumps are a well proven and much studied technology. In contrast to gas-fired boilers, heat pumps are most efficient when operating at low temperature and thus slow response heating systems (Li et al., 2012). This may be a positive aspect from the perspective of switching them on or off in a DR project. However, little research has been done on the technical and financial potential of domestic heat pumps on the FCR market. This research aims to investigate this technical and financial potential by answering the following research question:

*What is the technical and economic potential for a portfolio of aggregated domestic heat pumps to deliver flexibility on the Dutch FCR market?*

In this research, financial potential includes financial revenues and fines, whereas technical potential includes the bid quantity. Besides the financial and technical potential, the effects of market developments, regulations and comfort constraints processes on the potential for heat pumps to deliver flexibility are still to a large extent unknown. In addition, little research has been done on strategic bid methods that an aggregator can implement to maximize its revenue. To provide insights into these aspects, the following sub-questions are answered in this thesis:

1. *How can an aggregator improve its bidding strategy to optimize its revenue without compromising its relationship with the parties that procure flexibility? (see section 4.1 and 4.2)*
2. *How do market developments influence the potential for domestic heat pumps to deliver flexibility on the FCR market? (see section 4.4.1)*
3. *How do regulations set by grid operators influence the potential to deliver flexibility on the FCR market? (see sections 4.4.2, 4.4.3 and 4.4.4)*

## 1.3 Introduction to the methodology

To answer the above mentioned research questions, a quantitative model is developed in Python, in which historical frequency and heat pump data are used to simulate a switching and bid process. Data from 33 households is used and scaled up to mimic a portfolio of 20.000 households, holding 10 MW capacity on a 5 minutes resolution. Based on historical frequency measurements, the Required Flexible Power (RFP) for every 5 minutes was determined. Then, by fictively switching the heat pumps, the revenue and the fines were calculated for an iteratively increasing bid size. This process was performed for every week, leading to a revenue, fines and net revenue per week.

Three strategies are considered that the aggregator can apply to determine the weekly bid size:

1. **Reliable strategy**: The aggregator aims to choose the bid size in such a way that 100% availability and 100% reliability can be guaranteed.
2. **Optimization strategy**: The aggregator aims to select the weekly bid size in such a way that the net revenue (revenue minus total fines) is maximized. This is done in the model by iteratively increasing the bid size up to the point where the increase in fines exceeds the increase in revenue.
3. **Opportunistic strategy**: With this strategy, the aggregator uses revenue maximization methods (like with the optimization strategy), only based on IR-fines. In this case, the net revenue is calculated as the revenue minus IR-fines. NA-fines are not taken into account in this strategy. In practice, this can be done in two ways. Firstly, by having a back-up portfolio from which the power consumption is not switched and secondly, by misinforming the TSO about the portfolio's capacity and baseline. The opportunistic strategy is a theoretical strategy that is mainly taken into account to make the distinction between reliability and availability more visible.

## 1.4 Reading guide

After this introduction chapter, a theoretical framework is presented in which background information is provided regarding heat pumps, the European and Ducth electricity system and the FCR market ant its specifications. In the methodology chapter, underlying methods behind this model and the research are described. Chapter 4 presents the results, on which the conclusion in chapter 5 is based. In chapter 6, a reflection on the results, conclusion and methodology of this research is provided. Finally, in chapter 7, a list of literature is provided, followed by an appendix in chapter 8.

# 2 Theory

This chapter aims to provide background information about heat pumps as a flexible DR asset (section 2.1), the European and Dutch electricity system and its design (section 2.2) and the FCR market and its product specifications (section 2.3). Additionally, this chapter forms the basis for the methods for calculating the RFP and the fine regime, as they are implemented in the model.

## 2.1 Heat pumps as a flexible DR-asset

Heat pumps can generally be divided in two categories: ground sourced heat pumps and air sourced heat pumps. Both types of heat pumps can provide heat in the winter and cooling in the summer. Heat pumps are able to extract heat from one side (soil or air) and transport it to the heating system of a house (Krigger, 2001). By doing this, the heat energy that is delivered to the household can be much higher than the electrical energy being consumed by the heat pump. The ratio between the heat energy delivered and the electricity being used is called the Coefficient of Performance (COP).

The efficiency of a heat pump depends on the difference between the outside/ambient temperature and the temperature of the water that is supplied to the house. Therefore, the COP is not constant, but decreases with a higher difference between ambient temperatures and room temperature (Bertsch & Groll, 2008). Given their high efficiency, heat pumps are increasingly being used for domestic heat supply. Currently, the European Union counts 7,5 million heat pump installations, with an increase of 800.000 heat pumps each year. Even though it is widely recognized that heat pumps can be used as flexibility assets in DR-portfolio's, their flexibility is currently only rarely utilized in practice (Fischer et. al, 2017).

The main drawback of using heat pumps for DR-purposes lies in the comfort constraints of the end-users (Parkinson, 2011). To ensure the comfort of the end-users, the room temperature of the houses should stay within certain limits. In the model, this comfort constraint is taken into account in a simplified way by implementing a maximum switch time, thereby setting a limit to the time that the heat pumps can be switched for. How this maximum switch time is implemented in the model is explained in section 3.5.2.

## 2.2 The European and Dutch electricity system

As part of the European synchronous power system, the Dutch power system has a nominal frequency set-point at 50 Hz (Koliou et. Al, 2014). Failing to maintain the system frequency close to this nominal value may lead to the disconnection of different system components. This may destabilize the system, eventually leading to blackouts (van der Veen, 2012).

In case of an imbalance in production of electricity and demand the frequency will respond as follows. In case the demand is higher than the production, the frequency will drop. If the demand is lower than the production, the frequency will increase. In order to prevent this reaction, Automatic Generation Control systems are used to maintain the frequency at the desired 50 Hz (Wood & Wollenberg, 2012). These are examples of supply side control. This research is mainly focussed on the demand side of control systems.

The international electricity market can generally be divided in three sub-markets: wholesale, retail and balancing. In the wholesale market, suppliers can cover their consumption portfolio in advance through long-term, forward contracts. However, renewable energy production and electricity consumption are not entirely predictable. Therefore, in addition, daily and hourly contracts are required. On a smaller level, for each connection to the grid, a so called Balance Responsible Party (BRP) needs to be assigned. The wholesale market stops when BRPs submit their expected production and consumption to the TSO (Meeus et. Al, 2005). Afterwards, the balancing markets takes over, under the responsibility of the TSO. Balancing is defined by the European Network of Transmission System Operators (ENTSO-E) as “the situation after markets have closed (GC (gate closure)) in which a TSO acts to ensure that demand is equal to supply, in and near real time” (ENTSO-E, 2013, p. 3).

The combined markets for balancing are referred to as ancillary service markets. This group of markets is divided by ENTSO-E (2013) in three categories: frequency containment reserve (FCR), frequency restoration reserve and replacement reserve. This thesis focusses on FCR. FCR is activated automatically as a response to frequency fluctuations and needs to be able to respond within thirty seconds (Lampropoulos, 2014).

In the residential sector, it is common that the role of the BRP and the role of the supplier are taken by the same market party. A BRP bears the responsibility of balancing supply and demand for its portfolio of consumers. It has the obligation of reporting the expected consumption and production within its region to the TSO. In the case where an aggregator regulates consumption of a portfolio of electric assets, different strategies can be used. The aggregator can take the role of BRP, the role of supplier, or both (Lampropoulos et. al, 2017). However, for the model in this research, this decision is deemed irrelevant.

## 2.3 The FCR market

This research aims specifically on the potential of domestic heat pumps to deliver flexibility on the FCR-market. Therefore, TenneT’s product specifications and fine regime for the FCR market will form an important input for the model. Both are described in detail in the next two sub-sections.

### 2.3.1 Product specifications of the FCR market

In a study performed by Koliou et. Al (2014), it was found that DR is limited by three regulatory factors: a minimum bid size, minimum bid duration and binding up and downward bids. On the Dutch FCR market, all three factors apply and play a major role in the bid strategy that the aggregator applies. Therefore, all three factors are incorporated into the model. The most important specifications for the FCR market are described below and are based on a document describing the product specifications of the FCR market (Tennet, 2017).

<u>Bid period</u>

For the Dutch FCR market, bidding occurs on a weekly basis. This means that every week, a bid can be performed, with a new capacity. This capacity is valid for the entire week, meaning that the aggregator is expected to deliver reserve capacity based on the bid capacity and frequency. Not being able to do so results in a fine.

Minimum bid size

The minimum bid capacity for market entrance on the Dutch FCR market is 1 MW. This means that bids with a capacity lower than 1 MW will be rejected.

Full Activation Deviation

The Full Activation Deviation, in this report referred to as FAD is the frequency deviation at which full activation of the portfolio is required. On the Dutch FCR market, this is 200 mHz. This means that at a frequency deviation of 200 mHz, the portfolio should respond with 100% of the bid capacity, in the direction in which it is required. For any frequency deviation in between, the portfolio should respond proportionally. For example, when the frequency is 49.9 Hz, and the bid size of that week is 1 MW, the portfolio should react with 50% of the bid size, so 500 kW lower relative to the baseline.

Insensitivity range

On the Dutch FCR market, the insensitivity range is 10 mHz (or 5 mHz in both directions). This means that an error in frequency response of up to this range is allowed. As a result, the RFP has a upper and lower boundary of +- 2.5%. When the frequency is between 49.95 Hz and 50.05 Hz, reacting is not required.

FCR full activation time

The full activation time for the Dutch FCR market is 30 seconds, meaning that the portfolio should be able to deliver the bid capacity within this period of time. This is a strongly limiting factor for many technologies that have a high ramp up or down time. However, due to the 5-minute resolution of the data, the full activation time could not be taken into account in this research.

### 2.3.2 The fine regime for the FCR market

In the case that the aggregator is not available or not able to respond adequately, the aggregator will be fined by the TSO. To calculate how much the resulting fine is, regulations are used that are described in a framework agreement concerning primary reserve (TenneT, 2013). Two types of fines are distinguished, NA-fines and IR-fines. NA-fines result when the portfolio does not have sufficient capacity available, whereas IR-fines result when the aggregator does not respond correctly.

In article 8, section 3.A of the framework agreement, the fine regime for NA-fines is described as follows:

*"In the event of Non-Availability, supplier owes TenneT a Non-Availability Payment in proportion to the relevant Non-Availability period (which is rounded up to whole hours). The amount of the payment is calculated as follows: (10 x bid price x volume non-available power = Non-Availability payment). The bid awarded to supplier for the relevant period of the supply contract with the highest bid price is used as bid price."*

In this research, historical data was used from ENTSO-E regarding FCR prices. These prices are based on the highest bid price in the given period. Therefore, in this research, it is assumed that the bid price equals the FCR price.

In article 9, section 1 of the framework agreement, the fine regime for IR-fines is described as follows:

*"For each event where a power change (ΔP) of a technical unit is demonstrably (graph) insufficient: deduction of one 24-hour period payment (= sum of the awarded bids to the supplier for the week in question), in proportion with the primary reserve which is reserved for the technical unit in question (from allocation message of supplier). For every supply contract, the compensation for inadequate response by supplier to TenneT is maximized at 3 times the sum of the awarded bids to supplier for the week in question."*

How these two fine statements are interpreted and implemented in the model to calculate the IR-fines and NA-fines is described in section 3.5.4 of the methodology.

# 3 Methodology

This chapter describes the methodology used in this thesis, starting with a description of the bid strategies that are studied (section 3.1). Next, the methods for processing heat pump data (section 3.2.), as well as frequency data (section 3.3) are presented. Then, a description is provided of how the availability and NA-fines (section 3.4) and the reliability and IR-fines (section 3.5) are determined in the model. In addition, the methods behind the selection of the bid size for all three strategies are described in section 3.6. Next, a description is given of the methods behind the sensitivity analysis (section 3.7) and plotting and displaying the results (section 3.8). Finally, section 3.9 provides a visual illustration of the model.

## 3.1 Bid strategies

There are multiple strategies that aggregators can choose to determine how much they should bid on a given market. In practice, aggregators often determine the bid size based on simple, heuristic methods. In this research, three different strategies were adopted, that an aggregator might apply in practice: The reliable, optimization and opportunistic strategy. These strategies were compared in terms of revenue flows and bid size.

### 3.1.1 The reliable strategy

With this strategy, the aggregator values its relationship with the party to which it delivers flexibility over profit maximization. Therefore, following this strategy, the aggregator aims to deliver 100% reliability and 100% portfolio-availability. By doing so, the aggregator is always capable of delivering the requested flexibility that they bid for and will never be fined. Therefore, both IR fines as well as NA fines will be zero. Given the fact that the model used in this research is based on historical data, perfect knowledge about frequency and power consumption are assumed. This makes it possible for the aggregator in this model to successfully apply the reliable strategy and achieve 100% reliability and portfolio-availability. In practice, this strategy is the most likely strategy that any aggregator will aim for. However, it will not always be successfully implemented, since frequency and power consumption patterns can be unpredictable. In this research, the bid size that follows from the reliable strategy will be referred to as the “reliable bid size”. Bidding any lower than this will be irrational, since the net revenue will be decreased without an increase in reliability. When successfully following this strategy, the relationship with the party to which the aggregator delivers flexibility will be improved, but revenue flows will be suboptimal.

### 3.1.2 The optimization strategy

With this strategy, the aggregator determines its bid size solely based on profit maximization. This means that the aggregator will choose to increase its bid size as long as the increase in revenue exceeds the extra fines resulting from IR or NA. By doing so, a bid size will be chosen in which the net revenue (income – total fines) is maximal. In this research, this bid size is referred to as the “optimized bid size”. Bidding any higher than the maximum bid size would be irrational, since net revenue will decrease. This strategy lowers the portfolio-availability and possibly the reliability and might therefore be suboptimal for the aggregators relationship with the party to which it delivers its flexibility compared to the reliable strategy.

### 3.1.3 The opportunistic strategy

With this strategy, like with the optimization strategy, the aggregator aims for profit maximization by increasing its bid size as long as the increase in revenue exceeds the extra fines. However, with this strategy, NA-fines are not taken into account. Avoiding NA-fines can be done by either misinforming the TSO regarding the capacity and baseline of the portfolio or having a back-up portfolio that ensures 100% availability, but does not need to deliver flexibility. As a result, NA-fines will be zero, and the only limiting factor to the bid size will be the IR-fines, which the aggregator uses to optimize its net revenue. The bid size resulting from this strategy will be referred to as the “opportunistic bid size”. Since the aggregator accepts large amounts of IR-fines in order to achieve a maximum net revenue, this strategy is considered the least beneficial for the aggregator’s relationship with the TSO. In this research, this strategy is introduced as a hypothetical strategy that provides insight in the distinction between the two types of fines and their influence on the net revenue and bid size.

## 3.2 Selecting and processing heat pump data as an empirical base

### 3.2.1 Switching mechanisms and heat pump specifications

In order to use the flexibility of a pool of heat pumps, it is essential to understand the response of heat pumps to signals sent by the aggregator. In a research performed by Fischer et. Al (2017), an analysis of this response is presented. In addition, a so called Smart Grid-ready (SG-ready) scheme is defined, consisting of 5 possible signals that the aggregator can send to control the heat pumps. Since the thermal behaviour of households is not taken into account in this research, a simplified version of the SG-ready scheme developed by Fischet et. al (2017) is being implemented. In this simplified version, the heat pump can either be switched to maximum capacity or to minimum capacity.

Below, technical specifications are provided of the heat pumps used in this project. The heat pumps are air-sourced and the assumption is made that all heat pumps are equal and have the same technical specifications. In addition, it is assumed that the heat pumps do not have a backup heater. The minimum power consumption resulted from a preliminary analysis of the dataset. Since the lowest power consumption is 5 W, this will be considered the lower boundary. The heat pumps have a relatively low thermal and electrical capacity. Due to confidentiality issues, more specific information regarding the heat pump data used for this research can only be obtained via a request to the author of this report directly.

| | |
|---|---|
| Type/brand: | Inventum Ecolution Combi 50 |
| Maximum power required: | 500 W |
| Minimum power consumption: | 5W |
| Thermal reservoir capacity: | 50 L |
| Maximum output temperature: | 55 °C |

### 3.2.2 Selection and filtering of the main dataset

The total dataset that was available for this research consisted of 133 households, from which 9 variables and 52 sub variables were available. 33 households contained a heat pump and were therefore relevant for this research. From these households, only the variable 'INVENTUM', with sub variable 'ACTUAL_POWER_DEMAND' were used. This describes the power demand for the heat pump per 5 minutes.

Data was available between 2014 and 2017. However, until 01-09-2016, an aggregator was involved in the project, switching the heating systems of the households. Therefore, all data before this date was considered to be not clean and was therefore not used in this research. The heating season is considered to last from the first of October until the first of May. Therefore, data from 30 weeks was taken into account between 01-09-2016 and 01-05 2017. However, from the end of December until the beginning of February, no data was available. This likely has to do with measurement equipment, but the exact reason for the missing data was not shared by the data provider. As a result of this missing data, an 8-week gap occurs in this period, leaving 22 weeks of useful data. The week-dates and number of available households per week are presented in section 8.1 of the appendix.

### 3.2.3 Selection of available households

Due to unknown measurement errors, many gaps occur in the data and the start date and end date between which data is available varies strongly per household. Since the bid period as defined by TenneT is weekly, the dataset was split in files per week. Then, in order to check if a household has sufficient data available in a certain week, the following criterion was used:

*Each households needs to have at least 90% useful data available in a given week. If a household does not meet this criterion, data for that household for that week will not be taken into account in the model.*

In this context, useful data means a credible numeric value. To check if it seems credible, visual checks were performed for every case where the power consumption was constant for longer than an hour, as well as for all cases where the power consumption exceeds the minimum and maximum limits (5W and 500W). Data that did not seem credible was deleted. Maintaining this 90%-criterion led to different numbers of households per week. In order to perform a fair analysis, the number of households were scaled up so that for every week, the number of households (and thus the portfolio size) was equal.

### 3.2.4 Fill and delete gaps in the data

After filtering households with the 90% criterion in the previous section, a maximum 10% of the data per household per week was missing. For the model to operate effectively, no gaps may occur in the data. Every data point needs to have a numeric value that seems credible. To achieve this, gaps needed to be filled, or more data needs to be deleted when the gap is too long to fill in a representative manner. Two types of gaps were distinguished:

1. Short gaps with less than 60 minutes of continuous missing data
2. Long gaps, with more than 60 minutes of continuous missing data

The short gaps were filled using the python built-in function, 'nearest'. This means that every missing value is replaced by the nearest measured value in the dataset. As a result, half of the gaps is filled with the last measured value before the gap (front fill), whereas the other half is filled with the first measured value after the gap (backfill). For the long gaps, this method did not seem viable, since it would lead to long constant periods in the dataset. Because of this, and the fact that there were only a small number of long gaps, data from households that contain a long gap in a certain week was deleted for that week.

In the table below (table 1), the number of long gaps and short gaps that were filled or deleted is displayed. Filling of the short gaps led to no loss of data. In the case of long gaps, data was deleted for one household for one week. This led to the deletion of 5,2% of the dataset, which is more than the actual missing data (1,1%).

*Table 1: Division short gaps vs long gaps in the data set*

| | **Short gaps, < 60 minutes** | **Long gaps, >= 60 minutes** |
|---|---|---|
| **Amount** | 2778 | 36 |
| **Number of gaps** | 343 | 202 |
| **Percentage of the dataset** | 1.8% | 1.1% |

### 3.2.5 Extrapolation to meet requirement for bid size

Due to the methods described in section 3.2.3 and 3.2.4, the number of households from which data was available differs per week. An overview of the available households is presented in section 8.1.1 of the appendix. In order to make the model operate efficiently, the number of households needs to be the same per week. In addition, the total capacity of the portfolio of heat pumps was too low to bid on any reserve market. For these reasons, the portfolio of households was fictively scaled up to a size that would be viable to operate on the FCR market. This viable size was assumed to be a 10 MW portfolio, consisting of 20.000 households. This was done in two steps.

Each household in the model represents a column in a data-frame (DF). In order to mimic a real life situation, in which a large number of heat pumps is being switched by an aggregator, the number of households/columns needed to be increased. However, increasing the amount of columns to 20.000 would make the model too complex to run for any program. Therefore, the first step in the process was to scale up the amount of columns to 100, which would mimic a realistic aggregation level. To do this, every column was duplicated by a factor that gets the number of columns closest to, but does not exceed 100. To fill the last number of columns up to 100, households were randomly selected by the model. As a result, each week consist of a DF with 100 columns, each representing the heat pump power consumption profile of a single household.

To increase the total portfolio capacity, the power consumption of each column was multiplied by 200. After doing this, the portfolio consist of 100 households, with a total of 10 MW. This is the equivalent of 20.000 heat pumps with a capacity of 0.5 kW each.

## 3.3 Frequency data: implementation and analysis

### 3.3.1 Implementation of frequency data in the model

Frequency data was obtained from the French TSO, RTE, since this data was more easily available. Data was gathered for the same time period as the heat pump data was available: October 2016 – May 2017. Since both the Netherlands and France are connected to the Central Western Europe (CWE) grid (ENTSO-E, 2015), they are assumed to operate under the same frequency. The data from RTE contained data on a 10 second basis, which is a higher resolution than the household data. In order to reduce the complexity of the model, the model operates on the lower resolution of the household data, which is 5 minutes. Therefore, frequency data had to be resampled from 10 seconds to 5 minutes. To do this, two different methods were used, so that the effect of different resampling methods can be compared.

In this research, the first method to resample the frequency data is referred to as the 'actual method'. With this method, the value for every 5 minutes is taken, and all 10-second-values in between are deleted. The second method is a built-in method in Python, in this research referred to as the 'mean method'. Instead of taking the value per 5-minutes, this method calculates the mean for all 10-second intervals over a 5 minute period. To assess which resampling method gives the most representative results, a frequency distribution was performed for both methods and compared with the original 10-second-interval data set. The results are presented in section 4.3.

Since short term frequency deviations that occur within a 5-minute interval are flattened out by taking the mean, the mean method results in a frequency distribution that is more centered around 50 Hz. As a result, the average frequency deviation is reduced in comparison to the original dataset, leading to a decreased value for RFP and therefore an overestimation of the bid size and net revenue. With the actual-method, this is not the case, since selecting a data point for every 5 minutes results in a more random selection. These expectations are confirmed by the results of the frequency analysis (section4.3). For this reason, the actual method is considered as the most representative and is therefore used in this research.

### 3.3.2 Performing frequency analysis

A factor that has a major influence on the bid size and thus the potential for FCR is the Required Flexible Power (RFP). The RFP is strongly dependent on frequency fluctuations. Therefore, getting insights in frequency deviations over time is paramount to understand how the RFP influences the potential for FCR. For this reason, an analysis was performed on the frequency data that was used in the model, over the period October 2016 – April 2017. A distinction was made between the original data, which was on a 10 seconds resolution, and the 5 minute-data, which was a result of resampling the original dataset using the mean method and the actual method, as mentioned above. The same analyses were performed on the three datasets (original, mean and actual), so that the impact of different resampling methods could be observed and the most representative resampling method could be used for the model.

First, the average deviation relative to the target frequency (50 Hz) was calculated, as well as the maximum deviation measured. Using these numbers, the average and maximum portfolio activation percentage was calculated. Then, the frequency distribution was plotted for all three datasets, showing the frequency on the x-axis, against the occurrence (% of the entire dataset) on the y-axis. Frequency measurements were rounded to two decimals. Finally, the frequency deviation was plotted against the occurrence in the dataset. These analyses provide insights in how the frequency is distributed over time, and how much flexibility is required on average and in extreme cases. Seasonal dependency of grid-frequency is considered out of the scope of this research.

## 3.4 Determine portfolio-availability and NA-fines

In the rare event when the frequency deviation reaches the FAD, 100% flexibility is required. In these cases, the power consumption from the baseline should be shifted with the capacity of the bid size in the direction in which the frequency deviates; at a frequency of 50.2 Hz, the portfolio should be shifted with 100% flexibility upwards, whereas at 40.8 Hz the portfolio should be shifted with 100% flexibility downwards. Even though these events only seldomly occur, the aggregator is expected to always be prepared for such an event. Not being able to deliver 100% flexibility at any moment results in a NA-fine. In the model used in this research, the bid size is increased in steps until the criteria for all three strategies are being met. For every bid size, upper and lower boundaries are defined:

$$P_{upper} = P_{max} - bid\ size$$

And:

$$P_{lower} = P_{min} + bid\ size$$

Where:

$P_{upper/lower}$ = The upper and lower boundaries, expressed in kW

$P_{min/max}$ = The minimum or maximum power that the portfolio consumes

Bid Size = The bid capacity of flexibility for a specific week

When the power consumption exceeds those boundaries ($P > P_{upper}$ or $P < P_{lower}$), the portfolio is not able to deliver 100% flexibility in that direction, resulting in a fine. In that case, an NA-fine results, following the fine regime as described in section 2.3.2:

$$NAfine = 10 * FCR\ price * \frac{E_{NonAvailable}}{E_{week}} = 10 * FCR\ price * \frac{\left(P_{required} - P_{available}\right) * \frac{T_{min}}{60}}{Bid\ size * 168}$$

Where:

NAfine = The NA-fine resulting from a non-availability event on a 5 minute resolution

$E_{non\text{-}available}$ = The non-available energy, expressed in MW

$E_{week}$ = The total energy volume that should be delivered (bid price * hours per week)

$P_{required}$ = The RFP

$P_{available}$ = The available flexible power

$T_{min}$= The timerange of the NA-event, expressed in minutes. In the model, this was 5 minutes.

The total NA-fines per week were calculated as the sum over all NA-fines per 5 minutes. The availability was then calculated as the amount of NA-events divided by the amount of data points per week (2016 in this model, 5 minute interval). The availability therefore measures the fraction of the week in which the portfolio was able to deliver 100% flexibility, but does not provide information regarding the non-available energy or power(difference between $P_{required}$ and $P_{available}$).

## 3.5 Determine reliability and IR-fines

To determine the reliability and IR-fines at a given bid size, an assessment needs to be made for every timestamp in the model whether or not the portfolio was able to respond correctly. In contrast to NA-fines and portfolio-availability, the IR-fines and reliability strongly depend on the frequency, RFP and heat pump availability (HP-availability). In the next sections, a description is given of how the RFP is calculated and how the HP-availability is checked and updated. In addition, the switching methods are described and an interpretation of the IR-fines and the fines and reliability calculations are presented.

### 3.5.1 Calculating RFP

In order to determine how the portfolio of households should react to frequency fluctuations, TenneT's FCR product specifications, as described in Section 2.3.1, are incorporated into the model. In this research, the required portfolio response is expressed in terms of RFP. This describes the power that the portfolio should shift at each moment. A positive value for RFP means that extra power consumption is required, whereas a negative value for RFP means that the power consumption should be shifted down. In both cases, the power change is relative to the baseline. If the portfolio uses X kW of power at moment t and the RFP at that moment has value Y, then the shifted power consumption should have the value of X + Y. The RFP can be calculated by:

$$RFP(t) = Bidsize * \frac{F_{actual} - F_{target}}{FAD}$$

Since no more than 100% flexibility can be required, the RFP cannot exceed the(positive or negative) bid size. The upper and lower boundaries of the RFP can be calculated by:

$$RFP_{upper/lower}(t) = Bidsize * \frac{(F_{actual} \pm Insensitivity\ Range) - F_{target}}{FAD}$$

Where:

| | |
|---|---|
| $RFP_{upper/lower}$ | = Upper and lower boundaries of RFP (MW) |
| Bid size | = Bid capacity for that week (MW) |
| $F_{actual}$ | = Actual measured frequency (Hz) |
| Insensitivity range | = Maximum measurement error (mHz) |
| FAD | = Full Activation Deviation |
| $F_{target}$ | = Target frequency |

As explained in Sections 2.2 and 2.3, the target frequency in the Netherlands is 50 Hz, the Full activation Deviation is 200 mHz, with an insensitivity range of 50 mHz. As a results, the RFP depends on the Actual frequency and the bid size. The figure below (figure 1) presents the frequency response for the Dutch FCR market, based on TenneT's product specifications. On the Y-axis, the portfolio activation fraction is displayed, representing the percentage of the portfolio that should be activated at any given frequency. When this is negative, power should be shifted down, relative to the baseline. Multiplied by the bid size, it results in the RFP. This method is applied for every frequency measurement in the model, to calculate the RFP.

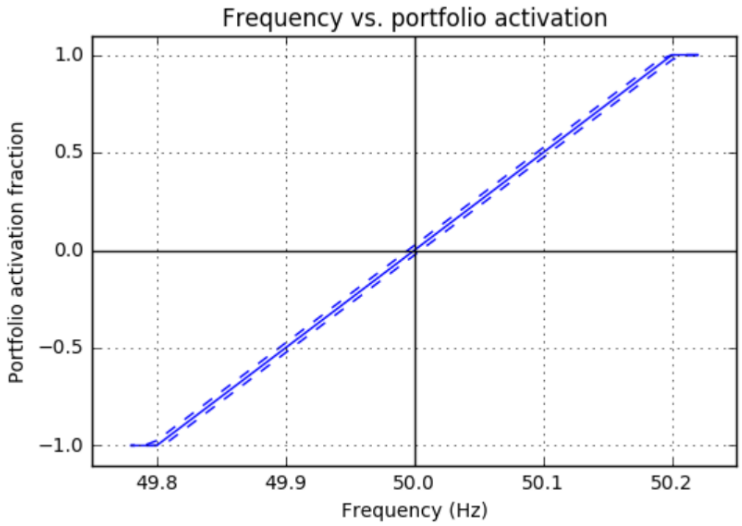



*Figure 1: Frequency response of a DR portfolio*

### 3.5.2 Checking and updating HP-availability

In the model, switching is limited to a maximum switch time, to implement comfort constraints. After a heat pump has been switched for the maximum switch time, it has to be non-active for a certain period that is n-times the maximum switch time, where 'n' is referred to as the 'non-activity factor'. During this time, the heat pump is not available for switching and has to follow the baseline consumption. In the default scenario, the maximum switch time is 15 minutes and the non-activity factor is 2. This means that after switching for 15 minutes, the heat pump is unavailable for switching for 30 minutes. When the heat pump is switched for 10 minutes, it cannot be switched for 20 minutes.

Checking HP-availability

Both upward and downward HP-availability will be stored in a DF, with timestamps on the vertical axis and households on the horizontal axis. The HP-availability can have three different states, based on which it can be checked whether or not a heat pump is available for switching in that direction:

- HP-availability > 0: In this case, the heat pump is available for switching but has been switched in the previous timestamp. The maximum switch time has not been reached. The value of HP-availability indicates for how many minutes the heat pump has been switched. E.g. + 10 means that it is still available, but has been switched for 10 minutes already.
- HP-availability = 0: heat pump is available for switching and has not been switched in the previous timestamp
- HP-availability < 0: heat pump is not available, needs to be non-active for the amount of time that the negative number indicates. E.g. -10, means that it can be switched after 10 minutes from now.

Updating HP-availability

When the heat pump is switched, 5 minutes are added to the (=> 0) value of HP-availability for that household for that moment. If the maximum switch time is reached, the positive value will be multiplied by -1 times the non-activity factor, making it non-active for twice the maximum switch time in the default scenario.

When the heat pump is not switched, 5 minutes are added to the value of HP-availability. If this value was already negative, it becomes less negative. When it becomes 0, the heat pump is available for switching again. However, when the heat pump is not switched and it has a positive value, the value will be multiplied by a factor -2. In this case, it will be non-active for twice the time that it has been switched. Finally, when the heat pump is not switched and the HP-availability has value 0, the HP-availability remains zero. In this case, the heat pump will remain available for switching.

In the figure below (figure 2), different options in the default scenario are displayed. The left column displays the action that is being performed (switched or not switched). Then, the value and status before updating are displayed as well as the value and status after updating. In the ‘comments-column’, explanation is being provided on that situation.

*Table 2: Value availability after switching or not switching*

| | before updating | | after updating | | comments |
|---|---|---|---|---|---|
| action | value | status | New value | New status | |
| Switched | 15 | Error | Error | Error | This situation should not be possible. When the maximum switch time is reached, the status should be set to unavailable. This indicates a bug in the code |
| | 10 | Available | -30 | Unavailable | Heat pump has been switched for the maximum switch time, is not available for twice the maximum switch time |
| | 5 | Available | 10 | Available | heat pump is still available, can be switched for 5 more minutes |
| | 0 | Available | 5 | Available | heat pump is still available, can be switched for 10 more minutes |
| | -5 | Error | Error | Error | This situation should not be possible. In this case, a heat pump is tried to be switched that is unavailable. This indicates a bug in the code |
| Not switched | 15 | Error | Error | Error | This heat pump should have been put to -30 earlier, since the maximum switch time will now be exceeded. This indicates a bug in the code |
| | 10 | Available | -20 | Unavailable | heat pump has been switched for 10 minutes, needs to be inactive for 20 minutes |
| | 5 | Available | -10 | Unavailable | heat pump has been switched for 5 minutes, needs to be inactive for 10 minutes |
| | 0 | Available | 0 | Available | Nothing changes, heat pump was and still is available |
| | -5 | Unavailable | 0 | Available | Inactivity time is over, heat pump is ready to be switched again |
| | -10 | Unavailable | -5 | Unavailable | Heat pump needs to be unavailable for 5 more minutes |
| | -30 | Unavailable | -25 | Unavailable | Heat pump needs to be unavailable for 25 more minutes |
| | -35 | Error | Error | Error | This situation should not be possible, since the availability cannot be lower dan -2 times the max Switch time. |

When a heat pump is switched in one direction, the availability-Df for that direction will be updated according to the ‘switched’ rules, whereas the availability-DF for the opposite direction will be updated according to the ‘not-switched’ rules. For every timestamp, every household needs to be updated.

### 3.5.3 Selection of heat pumps to be switched

Before switching, the model has to select the households that should be switched in a certain direction. Based on grid frequency, three situations can occur:

1. Frequency > 50.00 Hz (RFP > 0): heat pumps need to be shifted upwards. Available heat pumps will be selected from the availability-up DF. Heat pumps that are available, but are not switched, will be updated according to the ‘not-switched’ principle, described in section 3.5.2. All heat pumps in the availability-down DF will be updated according to the ‘Not-switched’ principle as well.
2. Frequency = 50.00Hz (rfp = 0): No heat pumps need to be switched. All heat pumps will be updated according to the ‘not-switched’ principle, in both directions.
3. Frequency < 50.00 Hz (rfp < 0): heat pumps need to be shifted downwards. Available heat pumps will be selected from the availability-down DF. Heat pumps that are available, but are not switched, as well as all heat pumps in the availability-up DF, will be updates according to the ‘not-switched’ principle.

Depending on the three above mentioned situations, division is made in two groups of available households, in the direction in which they need to be switched:

- Households with HP-availability > 0: these were switched in the previous timestamp, but are still available. These should be switched first, since switching households up to their maximum switch time is the most efficient, given the criteria explained in 4.5.1.
- Households with HP-availability = 0: these are available and were not switched in the previous timestamp. These should be switched only when all heat pumps that have availability > 0 are switched, and there is still not enough flexibility delivered (total Available Flexible Power (AFP) < RFP).

To find the heat pump that should be switched, the model first iterates over the households that have availability > 0 in the direction that they should be switched. Within this group, the algorithm looks for the heat pump that has the highest contribution of flexibility related to the RFP. It calculates for every heat pump the absolute difference between flexibility delivered (AFP) and required flexible power (RFP). The heat pump with the highest flexibility potential will be chosen as the selected heat pump to be switched.

### 3.5.4 The switching process

For the selected heat pump, the switching process follows the following steps:

- The flexible power delivered by the heat pump is added to the total flexible power delivered at that moment.
- The heat pump is updated according to the 'switched' principle
- The heat pump is removed from the list of available heat pumps. This list is generated again for every timestamp by the algorithm

To determine whether or not sufficient flexibility can be delivered at timestamp(t), a while loop will be used, in which the algorithm repeatedly executes a conditional code as long as a given condition is true. The condition in this case is 'total AFP delivered < RFP'. As long as the total AFP delivered is smaller than the RFP, insufficient flexibility is delivered, and more heat pumps need to be switched. The conditional code, consisting of the three steps mentioned above, will then be repeated. When the conditional statement becomes false, sufficient flexibility is delivered, and the code breaks out of the wile loop and continue to the next timestamp. This situation will be considered as a pass, and one iteration will be added.

However, in some cases, not sufficient heat pumps are available to deliver the RFP. In these cases, both lists of available households will become empty. If a situation occurs in which both lists are empty, and the while-condition is still not met, the code will break out of the loop and continue to the next timestamp. This situation will be considered as an IR-event, in which the portfolio does not respond adequately. In this case, one IR-event, as well as one iteration will be added. The costs for the IR-event can be calculated and added to the total fine.

To understand whether the upward or downward flexibility potential is limiting the optimum bid size and therefore the revenue, a division is made between upward-IR-events and downward-IR-events. Upward-IR-events occur when upward flexibility is deemed insufficient, whereas downward-IR-events occur when downward flexibility is deemed insufficient. The fine regulation for upward-IR-events and downward-IR-events are the same and are described in the next section 3.5.5.

When the portfolio uses on average more than half of its capacity during a week, upward flexibility is expected to occur more often, and upward-IR-events are more likely than downward-IR-Events. Vice versa, when the portfolio of heat pumps consumes only a small part of its capacity, downward-IR-events are more likely to occur, and downward flexibility will limit the maximum bid size.

### 3.5.5 **Calculate revenue and IR fines**

The revenue is based on the FCR price, expressed in €/MW/week. These prices are received from ENTSO-E (2018) and differ per week. In the period that is relevant for this research (September 2016-May 2017), prices range from €1,936.77/kW/week to €3,354.80/kW/week, with an average of €2,559.49/kW/week. A total overview of the FCR-prices per week can be found in the appendix in section 8.2. The revenue per week can then be calculated by:

$$Revenue_{week(x)} = Bidsize * FCRprice$$

In this research, an IR-event is defined as a 5-minute period in which the portfolio of heat pumps was not able to deliver sufficient flexibility. When an IR-event occurs, a fine from TenneT will result. The assumption is made here that every IR-event is directly notified by TenneT and will directly result in a fine, following the fine regime as stated by TenneT(2013), described in section 2.3.2. According to this fine regime, the fine per IR-event can be calculated as the percentage of delivered flexibility that was too low, multiplied by the revenue of one day:

$$Cost\ IR - event = \frac{RFP_{\frac{upper}{lower}} \_ FLP_{delivered}}{RFP} * \frac{Revenue_{total,week(x)}}{7}$$

Then, the total fine can be calculated by:

$$Fine_{total} = \sum_{weeks} Cost\ IRevent_{Week(x)}$$

The net revenue can be calculated by subtracting the total fine costs from the total weekly revenue:

$$Revenue_{net} = Revenue_{total,week(x)} - Fine_{total}$$

## 3.6 Determining the reliable, optimized and opportunistic bid size

For all three strategies, similar methods are used in the model to obtain the necessary information related to the specific strategy. The model iterates over a set of bid sizes until it reaches a bid size in which a criterion is met that is specific to one of the three strategies. For the main results, the bid size is increased in steps of 100 kW, starting with a minimum bid size of 100 kW. The reason for a relatively small bid size step is that it provides a high accuracy, resulting in smooth graphs and accurate main results. However, for the sensitivity analysis, a different bid size step is used to reduce the run-time of the model. In this section, the criteria for the three different strategies described, as well as the different iteration steps that are used for the sensitivity analysis.

### 3.6.1 Determining reliable bid size

With the reliable strategy, the aggregator aims to deliver 100% reliability and 100% availability, meaning that no NA-fines nor IR-fines are accepted. Therefore, the bid size is increased until the total fines are larger than zero. In that case, the model returns the results from the previous bid size, in which no fines occurred.

### 3.6.2 Determining the optimized bid size

With the optimized strategy, the aggregator aims to maximize its net revenue by increasing the bid size to the point where the previous net revenue is larger than the current net revenue. The previous net revenue is defined as the revenue minus the total fines for the most recent bid size iteration (current bid size minus bid size step):

$$Net\ revenue = Revenue - Total\ fines$$

### 3.6.3 Determining the opportunistic bid size

With the opportunistic strategy, the aggregator aims to maximize its net revenue, but avoids NA-fines by either communicating an incorrect baseline and portfolio capacity to the TSO, or having a back-up portfolio available that ensures the availability, but is not switched. With the opportunistic strategy, in the model, NA-fines are not taken into account. Therefore, the net revenue is defined as the revenue minus the IR-fines for the most recent bid size iteration (current bid size minus bid size step):

$$Net\ revenue = Revenue - IR\ fines$$

### 3.6.4 Bid size steps for the sensitivity analysis

For the sensitivity analysis, the model needs to be run for different parameter values, as described in section 3.7. With a high bid size, many iterations are needed before the bid size is found. Using a bid size step of 100 kW until the results for all three strategies are finished will lead to an unnecessary long run-time. Therefore, a more efficient method can be used with respect to the bid size when the model is running the sensitivity analysis. Therefore, in the sensitivity analysis, a bid size of 1 MW is used, until a rough estimation of all three strategies is found. In that case, the model iterates over a smaller bid size range (rough estimation +- 500 kW) with a bid size step of 100 kW, to get a more accurate approximation of the opportunistic bid size. Implementing this method will significantly decrease the run-time of the model.

## 3.7 Sensitivity analysis

The main results of the model show how the reliability, availability, fines and revenue flows are influenced by an increasing bid size. To obtain these results, multiple parameters are set with fixed values. The values of these parameters are based on literature, TSO documents or are in some cases heuristic. Since the values that are used for these parameters may influence the outcome of the results, it is important to investigate the effect of the parameters on the output. The sensitivity analysis aims to investigate this effect by running the model for different values of the parameters. By doing this, the 'sensitivity' of the output for different input values will become clear. This will give insight in the factors that affect the bid size and (net) revenue in the different strategies. For comparison, the total revenue over all weeks  was calculated for each value of the parameter. To determine the effect on the bid size and (net) revenue, the average bid size over all weeks will be compared for different parameter values. Section 3.7.1 will describe the parameters that will be included. In section 3.7.2, the default situation will be described, as well as values for the included parameters in the sensitivity analysis.

### 3.7.1 Parameters to be included

Given sub questions 2 and 3, as described in the introduction, the sensitivity analysis focusses on two factors: market developments and regulations. One parameter is included for market developments, the FCR price. For the TSO-regulations, three parameters are included in the sensitivity analysis: the IR-fine regime, the NA-fine regime and the FAD.

The FCR-price is a fixed price per week that the aggregator receives as a reward for its bid flexibility, expressed in €/MW/Week. Since the revenue is solely dependent on FCR prices and the bid size, and fines are strongly depended on the revenue, it is important to investigate the effect of FCR prices on all three strategies. Although the FCR price is constant over the week, it differs between weeks. In the sensitivity analysis, fixed FCR prices will be used that are the same for every week. It is expected that the FCR price will have a linear positive effect on the net revenue, but no effect on the bid size in all stratgies. Given the expected linearity of the relation, a limited number of values for FCR price will suffice.

IR-fines are calculated by deducing one 24-hour period payment for every IR-event, in proportion with the primary reserve which is delivered by the technical unit in question. In the sensitivity analysis, this rule can easily be altered by multiplying the amount of 24-hour periods (default is one) with a varying factor to see the effect on the results. The maximum fine rule is not taken into account in the sensitivity analysis. Since three times the sum of the rewarded bids would result in serious losses, this point will be per definition beyond the maximum bid size point and can therefore not limit the situation in both strategies. The NA-fine regimes are calculated as 10 times the FCR price multiplied by the volume of the non-available power. In the sensitivity analysis, the factor 10 can be replaced by different NA-fine regime factors, to investigate the effect on the output.

Finally, the full activation deviation describes the maximum frequency deviation at which the portfolio should be switched to 100% in both directions. The insensitivity range described how much the portfolio can be off the target power without being fined. Both are expressed in mHz.

### 3.7.2 Parameter values to be included

In the table below (table 2), the different values for all parameters that are included in the sensitivity analysis are displayed. The first row (bold) are the values that are taken into account in the default situation. For FCR price, the value in the default situations varies.

*Table 3:parameters and parameter values to be included in the report*

| **parameter** | **FCR price (€/MW/week)** | **NA-fine regime factor** | **IR-fine regime factor** | **FAD (Hz)** |
|---|---|---|---|---|
| **default value** | None | 10 | 1 | 0.2 |
| **values** | 1000 | 0.01 | 0.1 | 0.05 |
| | 2000 | 0.1 | 0.5 | 0.1 |
| | 3000 | 0.5 | 1 | 0.2 |
| | 4000 | 1.0 | 2 | 0.3 |
| | | 5.0 | 5 | 0.5 |
| | | 10.0 | | |
| | | 15.0 | | |
| | | 20.0 | | |
| | | 50.0 | | |

## 3.8 Plotting and displaying the results

To create the most value out of this research, it is important to display the results in an efficient way, so that a complete perspective on the results is provided, without showing too many graphs and figures, thereby losing the attention of the reader. In the general results, the average values over 22 weeks were displayed for all three strategies for the default situation of the model. This was presented in a table that forms the basis for answering the main research question. It should be noted that these values are averages over the heating season and are therefore not representative for a full year. Since displaying graphs for all weeks in this report was too much, one week was selected for which multiple graphs were displayed. To select the best week to display graphs for, visual inspection was performed on the graphs for all weeks and the week where the graphs are the most representative for all other weeks was selected. Week07, ranging from 2016-11-14 until 2016-11-20, seemed the most representative. Possible abnormalities in other weeks that do not match the graphs in week07 were mentioned. Graphs for other weeks can be requested by contacting the author of this report directly.

For week07, the power consumption of the portfolio, as well as the minimum and maximum bid size were displayed, as well as upper and lower boundaries resulting from the reliable and optimized strategy. This graph provides insights in how the power consumption changes over time and when NA-events occur. Additionally, the effect of the bid size on the availability and reliability of the scenario was displayed for week07. This provides valuable insights in the difference between reliability and availability and how they develop at an increasing bid size. Finally, monetary flows were presented for week07, displaying the revenue, fines and net revenue for all three strategies.

For the sensitivity analysis, the effects of each of the four parameters on the net revenue and on the bid size was presented. This was done by plotting for each parameter the value on the X-axis and the average bid size or net revenue over the 22 weeks on the Y-axis. To reduce the number of graphs, only the relevant graphs were displayed. Graphs that show no effect for any of the strategies (three horizontal lines) were not displayed. In that case, mentioning that the parameter has no effect on the bid size or net revenue was sufficient. Also, in the case where the parameter has a similar influence on the bid size as it has on the net revenue, only the bid size was displayed. In this case, it was mentioned that the effect on the net revenue showed a similar pattern.

## 3.9 Model visualization

### 3.9.1 The model

In the figure below (figure 3), a visualization of the model is presented. The orange blocks represent input in the model, whereas the green block represent the output of the model. The blue blocks represent the processes that occur in the model.

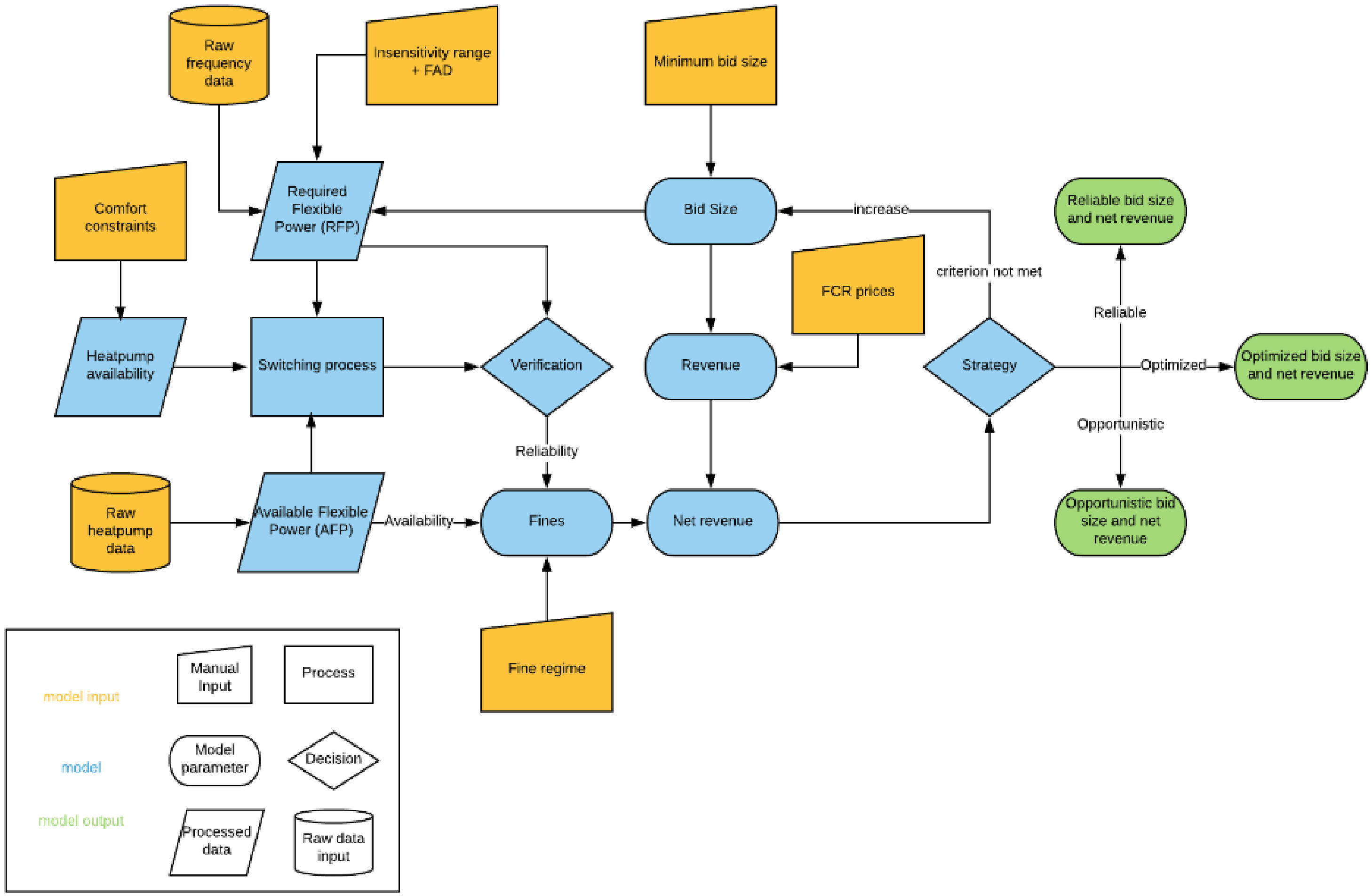



*Figure 2: visual illustration of the model used in this research*

### 3.9.2 **Model compartments**

In the table below (table 3), all the model compartments are described, including the type of component and the unit in which it is provided.

*Table 4:Description of the model compartments*

| | **Component name** | **Type of component** | **Description** | **unit** |
|---|---|---|---|---|
| Input | Raw heatpump data | Raw data input | Describes the power that is consumed by each device without interference of a third party aggregator | kW |
| | Raw frequency Data | Raw data input | Describes the frequency in the grid during a given time period | Hz |
| | Comfort constraints | Manual input | Describes the maximum switch time that is set to maintain the comfort of the residents | Minutes |
| | Insensitivity range + FAD | Manual input | Describes the Full activation deviation and insensitivity range, as set by the TSO | mHz |
| | Minimum bid size | Manual input | A minimum bid size that is manually selected, which forms the starting point of the bid size iterations | MW |
| | FCR prices | Manual input | The price that the aggregator receives from the TSO for delivering FCR | €/MW/Week |
| | Fine regime | Manual input | The TSO's regulation for fines as a result for inadequate response | - |
| model | Required Flexible Power (RFP) | Processed data | The required power change relative to het baseline at a given moment. Is based on frequency deviation and bid size | MW |
| | Available Flexible Power (AFP) | Processed data | The maximum up- or downward regulation potential for each heat device at a given time | kW |
| | Heatpump availability | Processed data | Describes whether or not, and for how long, the heat pump is available for switching | - |
| | Switching process | Process | The process of switching the heat pump, consisting of Checking availability, selecting available households, switch and update availability | - |
| | Strategy | Decision | The strategy that the aggregator implements to determine the bid size: Reliable, optimized or opportunistic | - |
| | Verification | Decision | Process that verifies whether, with a given bid size, the portfolio is able to respond adequatly (pass) or not (fail) | Binary |
| | Net revenue | Model parameter | The revenue deduced by the fines | €/Week |
| | Revenue | Model parameter | The revenue, calculated by multiplying the bid size with the FCR price | €/Week |
| | Bid size | Model parameter | The bid capacity in a certain week that the aggregator is bound to deliver | MW |
| | Fines | Model parameter | The fine that results from not being able to respons correctly | €/Week |
| Output | Reliable bid size and net revenue | Model parameter | The bid size and net revenue when the aggregator implements the reliable strategy, aiming for 100% availability and reliability | MW or €/week |
| | Optimized bid size and net revenue | Model parameter | The bid size and net revenu when the aggregator implements the optimized strategy, aiming for revenue maximization | MW or €/week |
| | Opportunistic bid size and net revenue | Model parameter | The bid size and net revenu when the aggregator implements the opportunistic strategy, aiming for revenue maximization solely based on IR fines | MW or €/week |

# 4 Results

This chapter presents the results of this thesis. It starts with a comparison of the three different bid strategies that are studied (par. 4.1). Thereafter, results on reliability and availability are given (par. 4.2). In par. 4.3, results of the frequency analysis are presented. This chapter ends with the results of the sensitivity analysis (par. 4.4).

## 4.1 General results, a comparison between different bid strategies

In the table below (table 4), a comparison is shown of the three strategies that are taken into account in this research. All values shown in the table are averages over the 22 weeks from which data was available. Values per week can be found in section 8.3 of the appendix.

*Table 5: Main results, comparison between different bid strategies. Based on averages over the 22 weeks*

| | Reliable | Optimized | Opportunistic |
|---|---|---|---|
| **Bid size** | 1,722 MW | 3,104 MW | 11,631 MW |
| **Revenue** | €4,322 | €7,851 | €29,324 |
| **Net revenue** | €4,322 | €6,872 | €24,437 |
| **Net revenue/household** | €0.21 | €0.34 | €1.22 |
| **IR-events** | 0 | 0 | 7 |
| **IR-up events** | 0 | 0 | 2 |
| **IR-down events** | 0 | 0 | 5 |
| **IR-fines** | €0 | €30 | €4,886 |
| **NA-fines** | €0 | €948 | €193,532 |
| **Total fines** | €0 | €978 | €198,418 |
| **Availability Percentage** | 100.0% | 90.0% | 0.3% |
| **Reliability** | 100.0% | 100.0% | 99.7% |

By using the reliable strategy, the aggregator successfully aims for a bid size that results in zero fines (NA and IR). As a result, the net revenue equals the revenue and both the availability percentage as well as the reliability are 100%. This strategy yields the lowest bid size and net revenue from the three strategies. With the optimized strategy, the aggregator aims to optimize its net revenue by accepting both NA- as well as IR-fines. By doing so, the net revenue and the average bid size are significantly higher compared to the reliable strategy Due to the fact that NA-fines occur at a much lower bid size compared to IR-fines, the amount of IR fines when the optimized bid size is reached is negligible: only one IR-event occurred in week 30, resulting in a fine of €662. The reliability therefore remains at (a rounded) 100%, whereas the availability percentage drops to 90%.

With the opportunistic strategy, the aggregator avoids €193,532 euro's NA-fine per week by misinforming the TSO about the baseline and the portfolio capacity, or by having a back-up portfolio that is only used for ensuring availability. In the model, the Na-fines that the aggregator would receive are calculated, but are not being used for determining the bid size and the net revenue. Therefore, the bid size and net revenue are solely limited by IR-fines. The bid size in this case is increased by 575% relative to the reliable strategy, and by 275% relative to the optimized strategy. The net revenue is increased by 465% relative to the reliable strategy, and by 256% relative to the optimized strategy. In this case, the aggregator is only rarely able to deliver the full bid size. In the model, only in week01, the bid size drops below 5 MW, resulting in an availability percentage of 7.1%. In all other weeks, the opportunistic bid size exceeds 5 MW, thereby dropping the average availability to 0.3%.

## 4.2 Reliability and availability, monetary flows and upper and lower boundaries to power consumption

In this section, graphs are provided of the reliability, availability, as well as monetary flows and the upper and lower boundaries of the power consumption at a certain bid size. These graphs were plotted for every week in the model. To limit the amount of graphs, one week is chosen for which the graphs are presented. The graphs are presented for week 07, ranging from 2016-11-14 until 2016-11-20.

### 4.2.1 Upper and lower boundaries to power consumption

In the graph below (figure 4), the power consumption (blue line) for week 07 is displayed, as well as the upper and lower boundaries for the reliable bid size (3100 kW) and the optimized bid size (3800 kW) in that week. For both bid sizes, horizontal dotted lines are plotted, representing the upper and lower boundaries for that bid size. The red dotted lines represent the upper and lower limit for the reliable bid size, whereas the green dotted line represents the upper and lower limit for the optimized bid size.

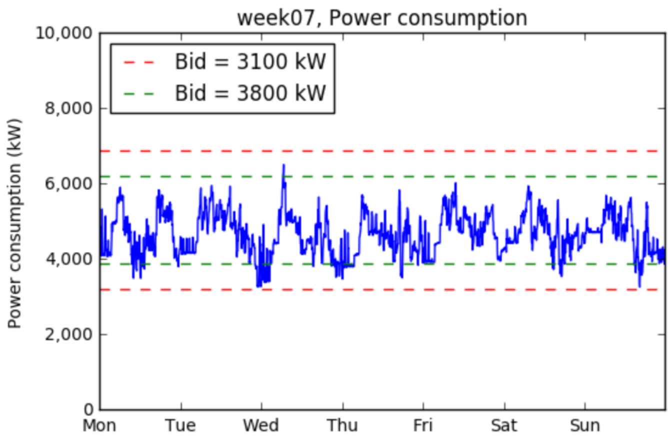



*Figure 3: Power consumption with upper and lower limits at given bid sizes*

The upper and lower boundaries are calculated by the methods explained in section 3.4 of this research. When the upper and lower boundaries are exceeded by the power consumption, NA-fines occur, since the portfolio is not able to deliver the required capacity corresponding with the bid size. As can be seen, with the reliable strategy, this does not happen, since the bid size is chosen in such a way that no fines will result, leading to an availability of 100%. The reliable bid size is therefore limited by the most extreme (upper or lower) values of the power consumption. With the Optimized strategy, the power consumption in some cases exceeds the upper or lower boundaries, resulting in NA fines.

When the bid size exceeds half the portfolio capacity (5 MW), the lower boundary will become larger than the upper boundary, making it impossible for the portfolio to remain between the boundaries and deliver the required flexibility. In these cases, the availability drops to 0% and an NA fines results for every measurement.  The NA-fines are assumed to be avoided with the opportunistic strategy. Due to the fact that the boundaries resulting from the opportunistic strategy are extreme, they are not displayed in this figure.

### 4.2.2 Availability and reliability against bid size

The portfolio-availability represents the fraction of the week in which the portfolio is able to deliver 100% flexibility, whereas the reliability represents the fraction of the week in which the portfolio responded correctly given the frequency and corresponding RFP. NA-fines correspond with portfolio-availability, whereas IR-fines correspond with reliability. The major difference between portfolio-availability and reliability is the fact that the reliability is strongly influenced by the frequency and RFP, whereas the portfolio-availability is solely dependent on the power consumption of the portfolio and the bid size.

In the figure below (figure 5), the availability (blue) and reliability (green) are plotted against the bid size in week 07. The green dotted vertical line represents the reliable bid size, whereas the blue dotted vertical line represents the optimized bid size and the red dotted vertical line represents the opportunistic bid size. Given the difference in range between the two, both are displayed on separate y-axis.

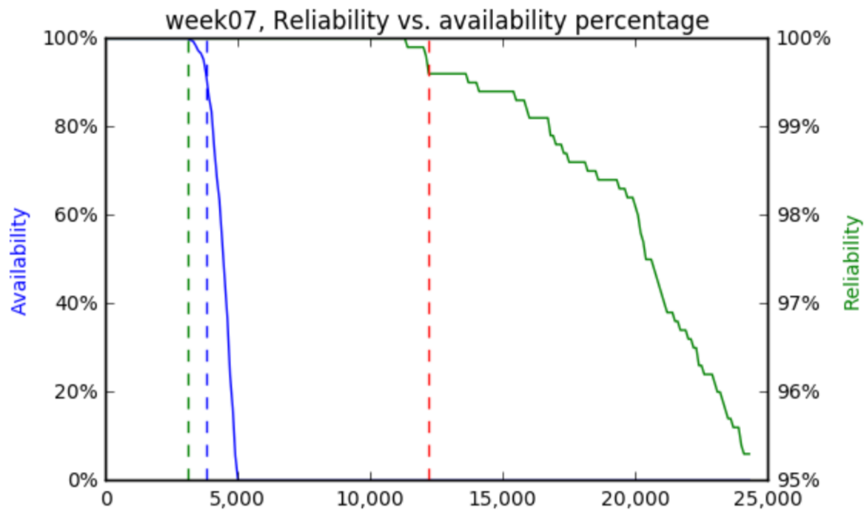



*Figure 4: Reliability vs availability at increasing bid sizes*

As can be seen, the availability shows a steep decrease, dropping from 100% availability at a reliable bid size of 3100 kW to a 0% availability at a bid size of 5,000 kW. The fact that the availability is reduced to 0% at a bid size of 5,000 kW can be explained by the fact that the portfolio will not be able to deliver 100% flexibility on a symmetrical market when the bid size exceeds half the maximum capacity. Therefore, in the model, the availability is in all cases reduced to 0% when the bid size exceeds 5,000 kW. In contrast to the availability, the reliability will not drop to 0%. Even at extremely high bid sizes, when the frequency is 50.0 Hz, zero flexibility is required and the portfolio will still be able to respond correctly. This frequency-dependency is the most-likely reason that the reliability shows a less-steep and later occurring decline compared to the availability. How often different frequency deviations occur is presented in section 4.3.

As mentioned, NA-fines correspond with the availability, whereas IR fines correspond with reliability. In the figure below, both NA-fines(blue) as well as IR-fines (green) are plotted against the bid size, in a different y-axis. The vertical dotted lines represent the reliable(green), optimized (blue) and opportunistic (red) bid size.

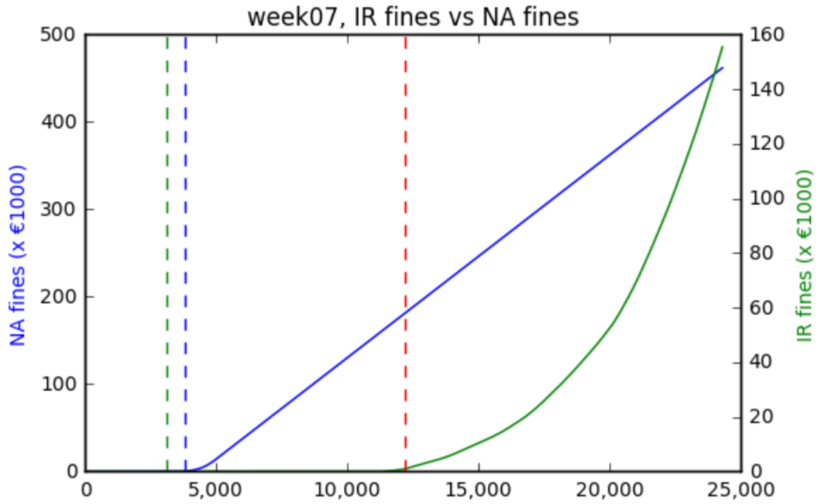



*Figure 5: IR-fines vs NA-fines at increasing bid sizes*

The above figure (figure 6) shows a positive relation between both fines and the bid size. The NA-fines increase linearly after 5,000 MW, whereas the IR-fines seem to increase exponentially. This difference can be explained by the fact that after 5,000 kW, availability drops to 0%, resulting in a NA-fine for every timestamp in the model. The fine is then linearly increased by the bid size. In the case of IR-fines however, the reliability does not drop to 0%. When the bid size is increased, not only the magnitude of the fine increases, but the amount of fines as well. This is most likely the main explanation for the non-linearity of the IR-fines. In addition, NA-fines are usually higher compared to IR-fines. This can be explained by the fact that, due to the non-dependency on frequency, NA-fines occur at a much lower bid size compared to IR-fines. Therefore, at 0% availability, NA-fines occur for every timestamp in the model. With IR-fines, this is not the case.

### 4.2.3 **Monetary flows**

In this section, the revenue, fines and net revenue are plotted against the bid size for both the reliable and optimized strategy, as well as for the opportunistic strategy. With the reliable and opportunistic strategy, the net revenue is calculated as the revenue minus the total (NA and IR) fines. With the opportunistic strategy NA-fines are avoided, so the net revenue is calculated as the revenue minus the IR-fines. In the figure below (figure 7), the revenue(green), total fines(red) and net revenue(blue) are displayed for week 07. In addition, the green dotted vertical line represents the reliable bid size, whereas the blue dotted vertical line represents the optimized bid size.

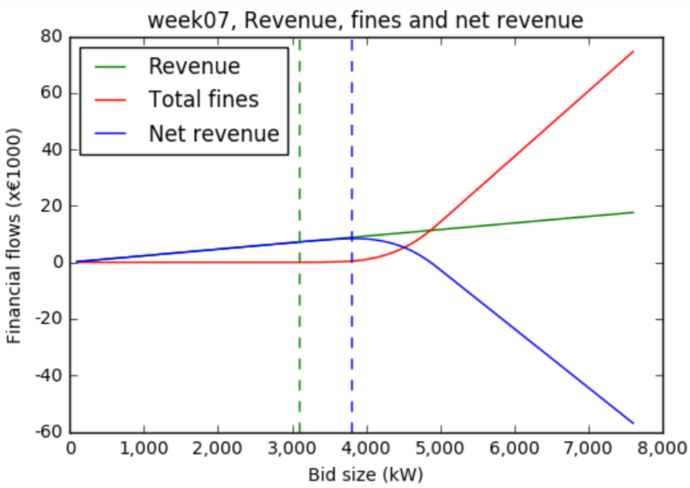



*Figure 6: Revenue, net revenue and fines for the optimized and reliable strategy*

The results show that the revenue increases linearly against the bid size, since it is calculated as the bid price multiplied with the FCR price. Until the reliable bid size is reached, the total fines are zero and the net revenue equals the revenue.  After the optimized bid size is reached, the increase in fines exceed the increase in revenue, leading to a decreasing net revenue. For the opportunistic strategy, in which NA-fines are not taken into account, a similar pattern can be observed. In this case however, the maximum net revenue is reached at a much higher bid size.

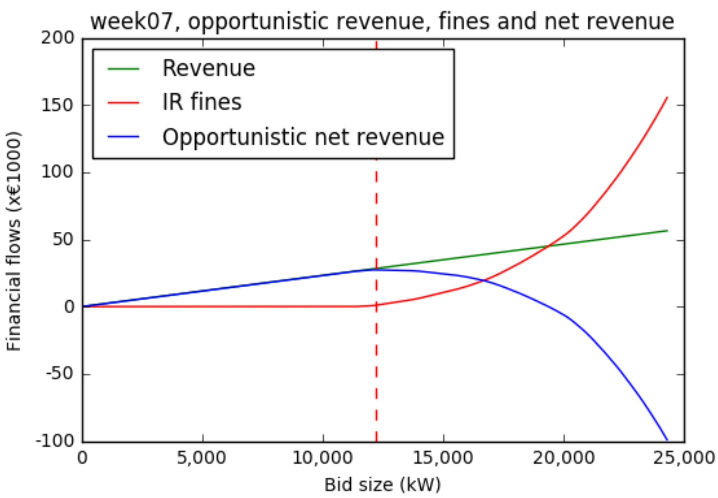



*Figure 7: Revenue, net revenue and fines for all three strategies*

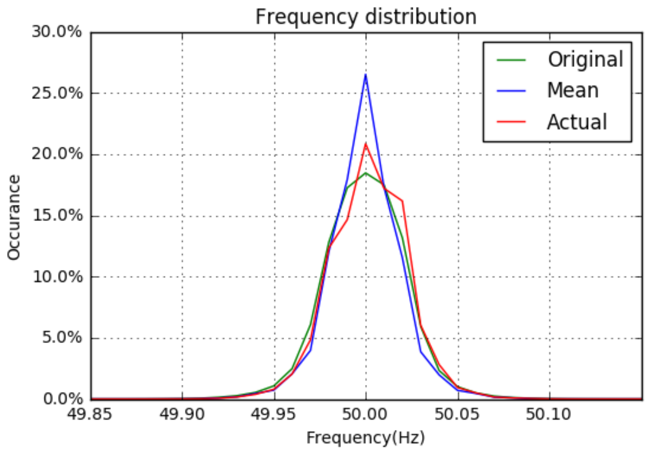
## 4.3 Frequency analysis

In the table below, the average and maximum deviation and portfolio percentage are displayed for the original dataset as well as for the dataset resulting from the actual and mean resampling method. As can be seen, both the mean and the actual resampling method have a decreasing effect on the average and maximum deviation, and thus on the portfolio activation percentage. This effect is significantly stronger in the mean resampling method, where the average deviation is 0.014 Hz against 0.017 Hz in the original dataset. This is probably due to the fact that when short term deviations occur within a 5 minute timeframe, they will not be represented in the mean value, as it is calculated by the mean method. For this reason, the actual resampling method is chosen as the most representative method. Given the small change in average deviation relative to the original dataset, the effect of the resampling methods on the main results are considered minimal.

*Table 6: Average and max deviation and portfolio %*

| | Average deviation | Max. deviation | Average portfolio activation | Max. portfolio activation |
|---|---|---|---|---|
| **Original** | 17 mHz | 140 mHz | 8.5% | 70.0% |
| **Mean** | 14 mHz | 110 mHz | 7.0% | 55.0% |
| **Actual** | 16 mHz | 110 mHz | 8.0% | 55.0% |

In the figures below (figure 9), two plots are shown, displaying the frequency distribution (right), and a distribution of the frequency deviation (left). In both cases, it is clear that higher deviations are more rare than lower deviations. This effect is visible to a larger extent in the mean dataset compared to the original dataset. Frequency deviations of 0.1 Hz, in which 50% of the portfolio needs to be activated, only seldomly occur.



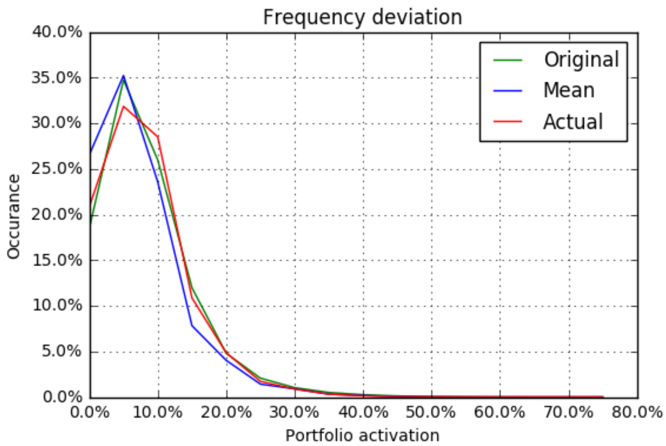




*Figure 8: Frequency deviation and frequency distribution*

## 4.4 Sensitivity analysis

The sensitivity analysis aims to answer the sub questions two, three and four, regarding the effects of market developments, comfort constraints and TSO regulations on the potential for domestic heat pumps to deliver flexibility on the FCR market. The potential for FCR is expressed in the bid size and the net Revenue. Average values for bid size and net revenues will be presented for different parameter values. Six parameters were taken into account.

### 4.4.1 FCR price

To research the effect of market developments, the FCR price was considered the most important parameter. The FCR price influences both the revenue as well as the IR and NA fine regime. For the main results, data regarding FCR prices was gathered from ENTSO-E, resulting in a varying FCR price over the weeks. In contrast, in the sensitivity analysis, different values for FCR price were used to run the model that were fixed per week. Four different values were used as input: €1000, €2000, €3000 and €4000 per MW per week.

Results show that the FCR price has no effect on the bid size in any of the three strategies. The graph shows three linear horizontal lines and is therefore not deemed relevant enough to be displayed in this report. An explanation for the fact that the FCR price has no effect on the bid size can be that the FCR price has a positive linear effect on both the magnitude of the fines as well as the revenue, but does not change the amount of fines. Therefore, the first fine (condition for the reliable strategy) and the point where the net revenues decrease (condition for optimized and opportunistic strategy) occur at the same bid size for different values of FCR price. However, as expected, the FCR price seem to have a linear positive effect on the net revenue, which is displayed in the figure below.

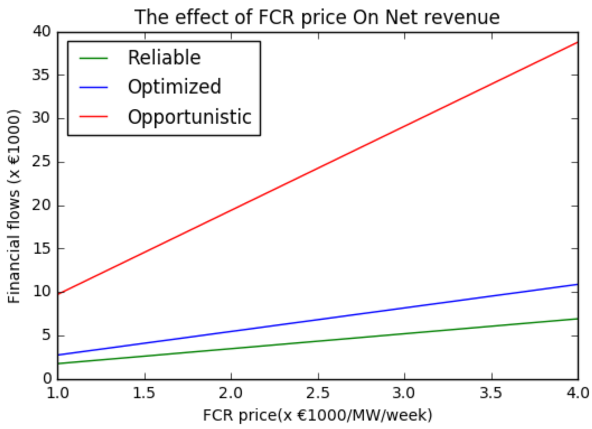



*Figure9: The effect of FCR price on net revenue*

As can be seen, the FCR price has a linear positive effect on the net revenue in all three strategies. The slope of the linear curves differ per strategy, with the strongest visible increase in the opportunistic strategy against the weakest linear increase in the reliable strategy. This can be explained by the fact that an increase in FCR price will amplify both the fines as well as the revenue. In the opportunistic strategy, the difference between the revenue and the net revenue is larger than with the other two strategies, leading to a stronger amplification of the net revenue and thus a steeper linear slope.

### 4.4.2 **FAD**

The FAD has a major impact on the RFP and therefore on the IR-fines. In the figure below (figure 11), the effect of the FAD on the bid size for all three strategies is displayed.

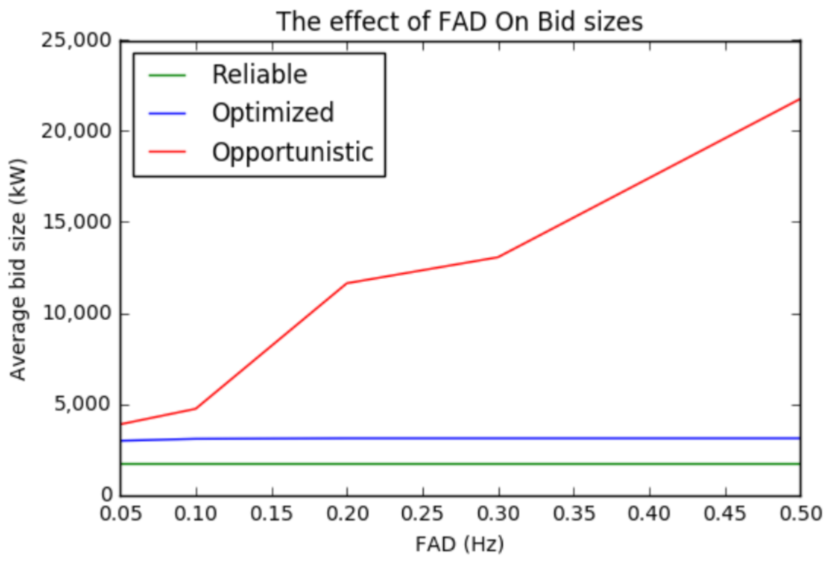



*Figure 10: The effect of the FAD on the bid size*

The FAD seems to have no visible effect on the bid size in the optimized and reliable strategy. With these strategies, the bid size is mainly limited by NA-fines, on which the FAD has no effect. However, a slight increase in the bid size is seen with the optimized strategy at low values of FAD (Section 8.4.2 of the appendix), that are too small to be visible in the graph. Possibly, when the FAD reaches extreme small values, the IR-fines will have a small influence on the bid size with the optimized strategy.

With the opportunistic strategy, the bid size is mainly limited by the IR-fines, and therefore influenced by the FAD. When the FAD is increased, IR-fines are decreased, leading to an increasing bid size. However, this relation seems partly linear, with some visible disturbances. The causes of these disturbances is unknown. The effect on the net revenue shows a similar pattern and is therefore not displayed here.

### 4.4.3 NA fine regime

An important factor regarding TSO regulations is the NA fine regime, being applicable in the case of non-availability. The main results are based on a NA fine regime factor of 10, as explained in section 3.4 of the methodology. For the sensitivity analysis, the model was executed for four additional values of NA fine regime factor: 1, 5, 15 and 20. The effect of the NA fine regime on the bid size is displayed in the figure below (figure 12).

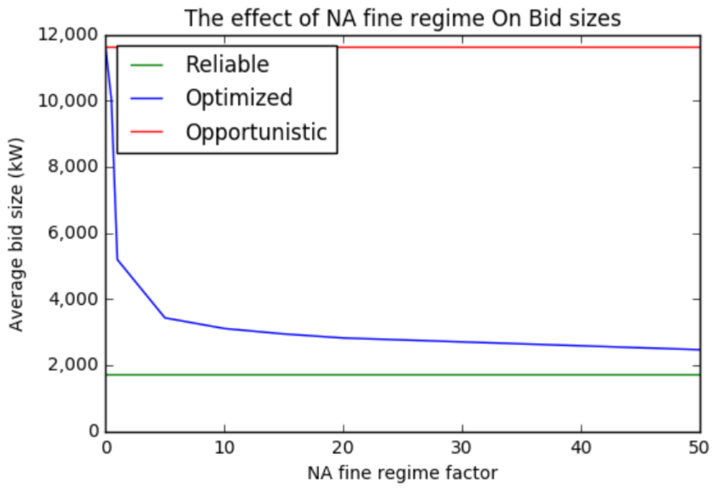



*Figure 11: the effect of NA fine regime on bid sizes*

As expected, the NA-fine regime does not influence the reliable and opportunistic bid size. With the reliable strategy, the bid size is limited to zero fines, making the magnitude of the fines irrelevant. With the opportunistic strategy, the NA-fines are not taken into account, since the aggregator is able to avoid NA-fines by sending falsified information to the TSO. With the optimized strategy, the NA-fine regime shows a decreasing negative effect on the bid size. At lower values of NA-fine regime factor, a steep decrease in bid size is observed, whereas less steep decreasing bid size can be observed at higher values of NA-fine regime factor

As can be seen, when the NA-fine regime factor approaches zero, the optimized bid size will approach the opportunistic bid size, since the weight of the NA-fines will be smaller. On the other hand, for an infinitesimally high NA-fine regime factor, the optimized bid size will approach the reliable bid size, since a NA-fine will almost directly lead to a loss in net revenue, making it equal to the reliable strategy where zero fines are accepted. For the net revenue, the graph shows a similar pattern, with similar explanations.

### 4.4.4 IR fine regime

Like the NA fine regime factor, an IR fine regime factor is taken into account, that can be used to display the effect of the IR fines on the bid size and net revenue. In the figure below (figure 13), the IR fine regime factor is plotted against the bid size.

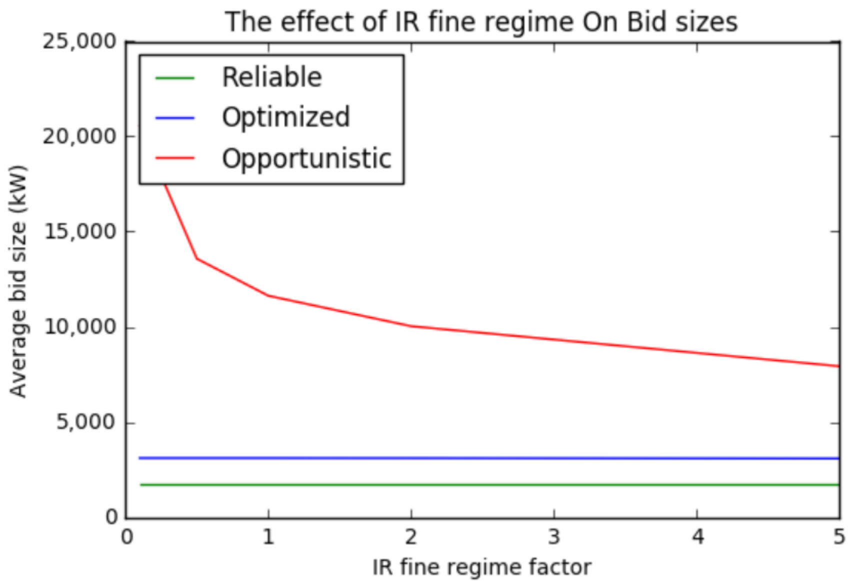



*Figure 12: The effect of the IR fine regime factor on the bid size*

The above figures shows that the IR fine regime factor has no effect on reliable and optimized bid size. With the reliable strategy, the bid size is chosen in such a way that no fines occur. The magnitude of the fine therefore has no influence on this process. With the optimized strategy, the bid size is relatively low, resulting in zero IR-fines, as mentioned in section 4.1. Therefore, the IR fine regime factor shows no effect on the optimized strategy. Both the optimized and the reliable strategy show a linear horizontal line.

The opportunistic bid size is strongly limited by the IR fine regime, since NA-fines are not taken into account. Therefore, with this strategy, the NA fine regime factor has a negative relation to the bid size. This effect is nonlinear and decreasing. A large IR fine regime factor will result in a small difference between the bid size with the opportunistic strategy relative to the optimized and reliable strategy. Eventually, if the IR-fine regime factor is high enough, zero IR-fines will be accepted. In that case, the bid size with the opportunistic strategy will be equal to the bid size with the optimized strategy. The effect of the IR fine regime factor on the net revenue shows a similar pattern and is therefore not displayed in this section.

# 5 Conclusion

This chapter aims to answer the research question and the main sub question. In section 5.1, general results are summarized to answer the main research question. Section 5.2 provides a description of the effects of the bid strategies, market developments and TSO regulations on the potential for FCR.

## 5.1 The technical and economic potential of domestic heat pumps

The main research question concerned the technical potential (expressed in average bid size), and the economic potential (expressed in net revenue) for heat pumps to deliver Frequency Containment Reserve (FCR). The results show that both the technical and economic potential depend strongly on the bid strategy:

- The net revenue resulting from this research is €0.21 per household per week h the reliable strategy, against €0.34 with the optimized strategy and €1.22 with the opportunistic strategy.
- Bid sizes vary from 1,722 kW with the reliable strategy to 3,104 kW with the optimized strategy and 11,631 kW with the opportunistic strategy.

These values are averages over 22 weeks in the heating season, ranging from 01-10-2016 until 01-05-2017, where 8 weeks of data were missing in December and January. Since December and January are usually the coldest months, they are expected to have the highest potential for delivering Frequency Containment Reserve with heating systems. This might slightly increase the average revenue. However, running the model for one full year of data would strongly decrease the average potential, since heat pumps do not provide heating in the summer.

Even though results show that a considerable amount of revenue could be created and flexibility could be delivered, this has to be divided over 20.000 households. In order to make such a project economically feasible, marginal costs per household need to be kept extremely low. This would be challenging for any aggregator. However, the households in this model were equipped with small heat pump systems that have a peak power of only 0,5 kW. Households with larger heat pumps will be able to deliver more flexibility, thereby lowering the amount of households, leading to lower costs. By focusing on projects with high-capacity heat pumps, the amount of households and therefore the investment costs can be reduced.

Since a strong correlation exists between outside temperature and heat pump capacity, the potential to deliver flexibility with heat pumps is strongly seasonally dependent. Results show that with this portfolio, 71% of the IR-events were IR-down events, which indicates that downward flexibility is a limiting factor in delivering FCR. A solution to this problem can be to create a combined portfolio with other assets where the upward flexibility is a strong limiting factor and that have opposite seasonal effects. A good example of such an asset may be cooling systems, which have a high potential in the summer and may have a higher downward potential.

## 5.2 The effect of bid strategies, market developments, comfort constraints and regulations

### 5.2.1 Bid strategies (RQ 1)

In this research, three strategies were compared on their potential for flexibility on the FCR market and the quality of the flexibility delivered. Results show that the bid strategy is the strongest factor of influence on both the potential and quality of the delivered flexibility. By successfully implementing the reliable strategy, the aggregator delivers 100% reliability and availability, resulting in zero fines by the TSO. Even though this strategy is highly beneficial for the aggregator's relationship with the Transmission System Operator, it results in a poor performance in terms of average net revenue and bid capacity. When the aggregator applies the optimized strategy through optimization of its net revenue by accepting fines as long as the net revenue increases, the performance in terms of net revenue and bid size is significantly higher. This results in a decrease in availability to an average of 90% while the reliability is maintained at 100%. When the aggregator applies the opportunistic strategy, net revenue can be increased by 465% compared to the reliable strategy, whereas the bid capacity can be increased by 575%. However, to achieve this, the aggregator has to avoid €194,000 Non-Availability fines per week by either sending falsified information to the Transmission System Operator, or having a back-up portfolio available.

### 5.2.2 Market developments (RQ 2)

In this research, the FCR price is considered as the most important factor that represents the market developments and is therefore taken into account as a parameter in the sensitivity analysis. Since the FCR price tends to both increase the revenue as well as the fines linearly, it has no effect on the bid size for any of the three strategies. However, the net revenue shows a linear positive relation to the FCR price. The slope between the linear increase in net revenue differs per strategy; The FCR price seems to have the strongest effect on the net revenue with the opportunistic strategy and the weakest effect with the reliable strategy. Since the FCR price is based on the highest bid in the market, it will be mainly based on future developments in the market for FCR. Based on these research, no predictions can be made on how the future FCR market and FCR prices will develop. It is clear however, that these developments have a major impact on the net revenue that an aggregator can make and therefore on the chance of success of future FCR project through demand response.

### 5.2.3 Regulations (RQ 4)

To investigate the effect of TSO regulations on the potential for FCR, three parameters were included in the sensitivity analysis; the NA-fine regime, the IR-fine regime and the FAD. Results show that the NA-fines have a significant influence on the bid size and net revenue in the optimized strategy, whereas IR-fines have a significant influence on the bid size and net revenue with the opportunistic strategy. Since with the reliable strategy, no 100% availability and reliability is delivered, both fine regimes do not influence the bid size and net revenue. Thus, it can be concluded that the effect of the fine regime on the potential for FCR is mainly dependent on the strategy that the aggregator implements. In the current situation, non-availability is heavily punished, thereby forming a strong limit to the flexibility that can be delivered. By shifting the burden from NA-fines to IR-fines, more flexibility can be delivered with the same assets, while still being reliable when the frequency deviations remain the same.

# 6 Discussion and recommendations for further research

This chapter aims to reflect on the methods, results and conclusion that result from this research. In section 6.1, strengths and weaknesses of this research are described. Section 6.2 provides recommendations for further research.

## 6.1 Discussion

### 6.1.1 The opportunistic strategy

Results show that NA-fines are a stronger limiting factor to the bid size and revenue than IR-fines. To make the effect of IR-fines on the bid size and revenue visible, an opportunistic strategy was implemented, in which NA-fines were not taken into account for the bid size selection process. By adding this strategy, more clarity is provided regarding the effect of the IR-fines and NA-fines separately on the bid size and revenue, and how reliability and availability develop when the bid size is increased. Two ways of avoiding NA-fines are mentioned: misinforming the TSO about the portfolio capacity and baseline, or having a back-up portfolio that ensures the availability, but is not switched. However, most likely, both ways will not be applied in practice often.

If the aggregator would have a back-up portfolio available, it is likely that more profit can be made if the combined portfolio (back-up + heat pumps) is seen as a mixed portfolio with which bids can be placed on the FCR-market or other markets. Therefore, using it as a back-up portfolio for ensuring the availability of the heat pumps seems like a loss of revenue. In addition, if this is done, the delivered flexibility by the combined portfolio cannot be assigned only to the heat pumps, since such high bids could not have been made by heat pumps alone. Given the absence of viable data, a back-up portfolio was not taken into account in the model.

The second way that is mentioned in the report is misinforming the TSO about the portfolio capacity and baseline. This is punishable by law (hence the fines) and might jeopardize the integrity towards the TSO. For these reasons, even though the net revenue is significantly higher with the opportunistic strategy and more flexibility can be delivered under the same circumstances, the advice resulting from this research will not be to apply the opportunistic strategy in real time. Even though applying the opportunistic strategy in practice might not be realistic, implementing it in the model resulted in valuable insights and can therefore still be seen as added value to the research.

### 6.1.2 Temperature boundaries

An important factor when switching heating systems for DR, that should be taken into account, is that the comfort of households should not be jeopardized. Not taking this factor into account may lead to loss of social acceptance. In the dataset, data was provided regarding in-house temperature and efficiency of the heat pumps. The original research plan was to use machine learning techniques to deduce the relation between heat pump power consumption, outside temperature and inside temperature. Then, while taking certain temperature boundaries as parameters, heat pump power consumption and inside temperature could be simulated, mimicking a real life situation. However, the data turned out to be of insufficient quality to perform this kind of simulation and machine learning techniques. No other dataset of higher quality could be made available within the time frame of this research project.

Therefore, instead of temperature boundaries, a limit was set in this model on the length that heat pumps could be switched without jeopardizing the comfort of the residents. This limit was set to 15 minutes. This is a heuristically chosen value. By implementing this, only the power demand of the heat pumps was needed from the dataset. After switching on the heat pump, it needed to be non-active for double the time that it was switched on. During this period, the power consumption of the heat pump follows the baseline, as it would have without any interference of a third party aggregator. To ensure that the temperature of a household ranges within pre-defined boundaries, a compensation algorithm should be implemented that, instead of following the baseline after switching, compensates for the loss in energy due to the switching process, by adding the same amount of energy that has been lost to the household. However, this would alter the baseline of the portfolio, which needed to be compensated for by other households. Implementing such a compensation algorithm would make the model too complex given the time and resources of this research project. Therefore, such a compensation algorithm is not taken into account in this research. In the current model, during the non-activity time, the heat pump simply follows the baseline.

### 6.1.3 Switching methods

The model used in this research is exclusively developed for the purpose of this research. It is therefore not tested by external parties or peer reviewed, and is to a large extent based on heuristics. The most important heuristics are the switching methods needed to determine the reliability and IR-fines, as described in section 3.5.4 of the methodology. In order to make the steps that the model takes during the switching process transparent, much effort has been done to describe the switching process in as much detail as possible. To check whether the code was producing the right output, tests have been run and error statements have been built into the model. In addition, during the process, the produced output was compared with the expected output to check whether the model operates properly.

### 6.1.4 Limitations due to low quality data and data resolution

An important factor for discussion in this research is the data quality and quantity. From the dataset, 33 households have installed heat pumps and were therefore relevant for this research. The quality of the data regarding these 33 households was less than expected beforehand, since the data contained many gaps and periods with constant values. According to the methods in section 3.2, these gaps and constant values were either filled or deleted. With the filling method for short gaps, these methods are not expected to influence the output and therefore the conclusions of this research significantly. However, much data has been deleted, thereby decreasing the amount of viable data. As a result, the sample size of the data was low. To correct for this small sample size, the portfolio of households have been scaled up to mimic a larger portfolio. By doing so, data has been duplicated and multiplied by a multiplication factor to generate a 10 MW portfolio. This process might influence the results of this research. With the frequency data, these problems did not occur. No gaps were found in the frequency data and all values seemed viable on a first evaluation.

Another factor that may influence the outcome of this research is the resolution of the dataset. The household data was provided on a 5 minutes basis, whereas the frequency data was provided on a 10 second basis. In order to reduce the complexity of the model, the 5 minute resolution was used as the resolution for the model. The frequency data was therefore down sampled from 10 seconds to 5 minutes, using the methods described in section 3.3. As a consequence, short term frequency fluctuations (within a 5 minute framework) have not been taken into account.

### 6.1.5 Parameters in the sensitivity analysis

In the sensitivity analysis, for every parameter value that is taken into account, the model has to go through the 22 weeks once. Given the high complexity of the model, this takes time and chances for bugs are high. Therefore, the amount of parameters and values that could be included in the sensitivity analysis is limited. For this research, four parameters were included, with a total of 23 values. This means that the model had to be run 23 times for different values of the sensitivity analysis. Possibly, other parameters might have been interesting to be included in the sensitivity analysis, providing insights in how the model operates. For example, the effect of the maximum switch time, non-activity factor and the insensitivity range on the results remains unknown, and is therefore recommended for future research.

### 6.1.6 Other simplifications

In the model, an IR-event or NA-event occurs when the portfolio is not able to respond properly or when insufficient flexibility is available on a 5 minute interval. With a higher resolution of the data, the dataset will consist of more data points and the amount of IR- or NA-events and therefore the fines are likely to increase. TSO regulation about what is considered as one IR-event or NA-event seemed ambiguous. In addition, the model holds the assumption that an IR-event or NA-event will lead to a fine in all cases. In practice however, this might not be the case, since TSOs do not have the capacity to discover every IR- or NA-event and respond with the fine regime adequately. An important FCR specification that is not taken into account in the model is that the portfolio should be able to respond with full capacity within 30 seconds. Due to the 5-minutes data resolution, this specification could not be taken into account. For these reasons, the number of IR-events and NA-events, as well as the resulting fines in this model are considered a rough estimation. To get more accurate results, more specific information regarding the fine system is required, as well as a higher resolution and a higher quality of the dataset. The verification process can then be altered in such a way that it more precisely represents the verification methods that TenneT uses and the way the fine regime is enforced.

In this research, the number of households that were available per week ranges between 11 and 22. After multiplication, households were duplicated until 100 households per week were reached. As a result, heat pump profiles were duplicated that follow the same consumption pattern. In practice, this is unlikely. If 100 unique households were used in the model, the power consumption would have been more stable, leading to a higher potential to deliver FCR. To solve this problem, a larger dataset that is of higher quality is required.

In an advanced phase of this research, it became clear that the heat pumps were complementary to installed gas heating systems, from which no data was available. It was not clear how the heat pump system was integrated with the gas boiler so that they together provide a heat profile that delivers a constant comfortable temperature. This problem contributed to the decision to reject all data except for the power consumption variable. The assumption was made that even with a gas boiler with unknown behavior, the heat pump power consumption profiles could still be deemed representative for a heating system in which only a heat pump provides the required heat for the household.

In this research, a portfolio is taken into account consisting solely of domestic heat pumps. In practice, it is unlikely that an aggregator will bid on the FCR market with a portfolio consisting solely of heat pumps. This will be suboptimal, given the high seasonal dependency and the fact that combining heat pumps with other DR-assets will increase the potential for FCR.  By combining the heat pumps in an integrated portfolio, the added revenue and flexibility delivered by the heat pumps will most likely by higher than with this single-type asset portfolio.

## 6.2 Recommendations for further research

In order to have more accurate results, a dataset of higher quality is required. With such a dataset, the machine learning technique as mentioned earlier could be used to estimate the effect of heat pump power consumption on room temperature. With this effect known, households and their temperature behavior could be simulated, mimicking a real life situation to a much higher accuracy. This approach would solve numerous problems that occur within this research. First of all, the aggregation effect could be better observed, since the simulated households will not be duplicated and will each have a unique baseline. In addition, the maximum switch time, non-activity time and compensation algorithm will not be necessary, since the simulation will ensure that the temperature inside the households is kept within certain boundaries. Filling up gaps in the data will not be necessary either, since the power consumption profiles will in this case not be based on real data, but will be simulated. Instead of using real data to simulate the effect of power consumption on inside temperature, an alternative solution would be to create a thermodynamic model that simulates household behavior based on insulation values and outside temperature. Both solutions for simulation models did not seem viable in this research, due to time constraints and the absence of viable data.

In the sensitivity analysis, the effects of market developments, regulations and comfort constraints on the potential to deliver FCR were considered. In total, six parameters were included. In future research, this can be expanded. In the model, bidding occurred on a weekly basis, and all data was divided in weekly periods. To research the effects of a change in the bid period, this could be taken into account as a parameter in the sensitivity analysis. Due to time limitations, this was not possible in this research. Furthermore, on the FCR market, a minimum bid size of 1 MW is required. To meet that criterion, the portfolio in the model was scaled up to a 10 MW portfolio, in which the minimum bid size would not form a limiting factor. In future research, the effect of the minimum bid size on market penetration can be researched. Additionally, an important limiting factor for delivering FCR seemed to be the binding of up and downward bids. As an additional parameter in the sensitivity analysis, a scenario could be created where up and downward bids would be decoupled, creating both a fictive FCR-up and FCR-down market. This was not possible within the time limits of this research.

Besides simulating temperature with a dataset of higher quality, further research could aim on a shorter resolution of the data and a more accurate implementation of the fine regulations of TenneT. With a shorter resolution, the effect of the 30 seconds rule could be investigated. Also, more specified information about when an IR- or NA-event is fined as one single event or as multiple different events can be implemented. In many cases however, this fine system is not defined to such a level of detail by the System Operator, since it is to a large extent based on trust. A smaller resolution of the data would require more efficient coding and more computational power, since it would drastically increase the computation time of the model.

Results from this research show that there the NA-fines are a stronger limiting factor to the bid size and revenue compared to IR-fines. In practice, this means that the aggregator receives high fines for not being able to deliver 100% flexibility, while this situation only seldomly occurs. This raises the question whether the current fine regimes for the FCR market are the most effective way of ensuring FCR quality. Possibly, more flexibility can be unlocked with DR-assets by restructuring the FCR regulations and fine regime. Further research can aim on investigating the quality and potential of FCR by DR with a different regulation structure.

In this research, availability fines are based on the most extreme values for power consumption. With the reliable strategy, the bid size is directly limited by extreme values of power consumption; In this case, when the power consumption reaches the minimum power (even for 5 minutes), the bid size is reduced to zero, because no downward flexibility can be delivered. To overcome this problem, an aggregator can apply peak shaving methods on the baseline, by creating a more constant power consumption profile. This will be highly beneficial for the amount of NA-fines and therefore for the bid size. However, creating such an algorithm was too complex given the time and resources of this research and is therefore considered a recommendation for further research.

The scope of this research lies on the potential for domestic heat pumps to offer flexibility on the FCR market. Further research could build on this by extending the model to operate on other markets or other technologies as well. In the Netherlands, the model could be extended to secondary or tertiary reserve, other technologies and the effect of combining different technologies on other markets. Eventually, comparisons can be made between countries and their regulations, to determine how the balancing system can be optimized at a European level. Also, the model can be used as a tool to predict on which markets, with a given portfolio, the most profits can be made.

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# 8 Appendix

In the appendix, anything that is relevant for this research, but could not or should not be presented in the main document is presented. Section 8.1 provides a table with the number of households that have viable data per week. In section 8.3, an overview is given of the FCR prices per week. In section 8.3, tables are provided with the main results per week, that form the basis behind the general results in section 4.1 of this report. Finally, section 8.4 provides tables with the data behind the graphs that are displayed in the sensitivity analysis in section 4.4.

## 8.1 Processing heat pump data

### 8.1.1 Number of households per week

*Table 7: The number of available households per week*

| From | To | Households | Without gaps | Deleted | |
|---|---|---|---|---|---|
| 1 | 3-10-2016 | 10-10-2016 | 22 | 21 | 1 |
| 2 | 10-10-2016 | 17-10-2016 | 20 | 20 | 0 |
| 3 | 17-10-2016 | 24-10-2016 | 22 | 19 | 3 |
| 4 | 24-10-2016 | 31-10-2016 | 23 | 23 | 0 |
| 5 | 31-10-2016 | 7-11-2016 | 19 | 18 | 1 |
| 6 | 7-11-2016 | 14-11-2016 | 19 | 19 | 0 |
| 7 | 14-11-2016 | 21-11-2016 | 24 | 24 | 0 |
| 8 | 21-11-2016 | 28-11-2016 | 23 | 22 | 1 |
| 9 | 28-11-2016 | 5-12-2016 | 21 | 21 | 0 |
| 10 | 5-12-2016 | 12-12-2016 | 22 | 19 | 3 |
| 11 | 12-12-2016 | 19-12-2016 | 21 | 20 | 1 |
| 12 | 19-12-2016 | 26-12-2016 | 21 | 0 | 21 |
| 13 | 26-12-2016 | 2-1-2017 | 0 | 0 | 0 |
| 14 | 2-1-2017 | 9-1-2017 | 0 | 0 | 0 |
| 15 | 9-1-2017 | 16-1-2017 | 0 | 0 | 0 |
| 16 | 16-1-2017 | 23-1-2017 | 0 | 0 | 0 |
| 17 | 23-1-2017 | 30-1-2017 | 0 | 0 | 0 |
| 18 | 30-1-2017 | 6-2-2017 | 0 | 0 | 0 |
| 19 | 6-2-2017 | 13-2-2017 | 13 | 0 | 13 |
| 20 | 13-2-2017 | 20-2-2017 | 16 | 16 | 0 |
| 21 | 20-2-2017 | 27-2-2017 | 16 | 16 | 0 |
| 22 | 27-2-2017 | 6-3-2017 | 15 | 13 | 2 |
| 23 | 6-3-2017 | 13-3-2017 | 19 | 17 | 2 |
| 24 | 13-3-2017 | 20-3-2017 | 20 | 19 | 1 |
| 25 | 20-3-2017 | 27-3-2017 | 19 | 16 | 3 |
| 26 | 27-3-2017 | 3-4-2017 | 19 | 19 | 0 |
| 27 | 3-4-2017 | 10-4-2017 | 22 | 17 | 5 |
| 28 | 10-4-2017 | 17-4-2017 | 22 | 20 | 2 |
| 29 | 17-4-2017 | 24-4-2017 | 23 | 22 | 1 |
| 30 | 24-4-2017 | 1-5-2017 | 19 | 19 | 0 |
| **Total** | | | **480** | **420** | **60** |

## 8.2 FCR prices

In the table below, the FCR prices per week are displayed. Prices were received form Entso-e(2018), in €/week. When divided by the total delivered flexibility in MW, the average price in €/MW/week was calculated. In week9 (marked yellow), the total delivered flexibility was missing. Therefore, the weekly price was calculated as the average price over the other weeks. The area in the table that is marked red displays weeks in which price data was available, but household data was not. In these weeks, the price data was therefore not used.

*Table 8: FCR price calculations per week*

| Week | From | To | €/week | Delivered MW | €/MW/week | €/kW/week |
|---|---|---|---|---|---|---|
| week01 | 05.09.2016 00:00 | 12.09.2016 00:00 | € 146.909,04 | 72 | € 2.040,40 | € 2,04 |
| Week02 | 12.09.2016 00:00 | 19.09.2016 00:00 | € 147.194,52 | 76 | € 1.936,77 | € 1,94 |
| week03 | 19.09.2016 00:00 | 26.09.2016 00:00 | € 97.291,47 | 50 | € 1.945,83 | € 1,95 |
| week04 | 26.09.2016 00:00 | 03.10.2016 00:00 | € 154.492,58 | 75 | € 2.059,90 | € 2,06 |
| week05 | 03.10.2016 00:00 | 10.10.2016 00:00 | € 107.959,18 | 50 | € 2.159,18 | € 2,16 |
| week06 | 10.10.2016 00:00 | 17.10.2016 00:00 | € 109.591,34 | 50 | € 2.191,83 | € 2,19 |
| week07 | 17.10.2016 00:00 | 24.10.2016 00:00 | € 133.762,46 | 57 | € 2.346,71 | € 2,35 |
| week08 | 24.10.2016 00:00 | 31.10.2016 00:00 | € 85.568,34 | 35 | € 2.444,81 | € 2,44 |
| week09 | 31.10.2016 00:00 | 07.11.2016 00:00 | € 190.609,47 | Missing | € 2.559,49 | € 2,56 |
| week10 | 07.11.2016 00:00 | 14.11.2016 00:00 | € 83.863,03 | 35 | € 2.396,09 | € 2,40 |
| week11 | 14.11.2016 00:00 | 21.11.2016 00:00 | € 180.765,03 | 78 | € 2.317,50 | € 2,32 |
| week12 | 21.11.2016 00:00 | 28.11.2016 00:00 | € 82.783,44 | 35 | € 2.365,24 | € 2,37 |
| week13 | 28.11.2016 00:00 | 05.12.2016 00:00 | € 119.525,16 | 50 | € 2.390,50 | € 2,39 |
| week14 | 05.12.2016 00:00 | 12.12.2016 00:00 | € 123.174,50 | 50 | € 2.463,49 | € 2,46 |
| week15 | 12.12.2016 00:00 | 19.12.2016 00:00 | € 120.428,16 | 50 | € 2.408,56 | € 2,41 |
| week16 | 19.12.2016 00:00 | 26.12.2016 00:00 | € 222.198,88 | 80 | € 2.777,49 | € 2,78 |
| week17 | 26.12.2016 00:00 | 02.01.2017 00:00 | € 345.544,36 | 103 | € 3.354,80 | € 3,35 |
| week18 | 02.01.2017 00:00 | 09.01.2017 00:00 | € 233.232,07 | 74 | € 3.151,78 | € 3,15 |
| week19 | 09.01.2017 00:00 | 16.01.2017 00:00 | € 158.128,09 | 53 | € 2.983,55 | € 2,98 |
| week20 | 16.01.2017 00:00 | 23.01.2017 00:00 | € 155.498,06 | 51 | € 3.048,98 | € 3,05 |
| week21 | 23.01.2017 00:00 | 30.01.2017 00:00 | € 137.729,25 | 43 | € 3.203,01 | € 3,20 |
| week22 | 30.01.2017 00:00 | 06.02.2017 00:00 | € 166.466,00 | 56 | € 2.972,61 | € 2,97 |
| week23 | 06.02.2017 00:00 | 13.02.2017 00:00 | € 147.321,34 | 50 | € 2.946,43 | € 2,95 |
| week24 | 13.02.2017 00:00 | 20.02.2017 00:00 | € 130.377,09 | 45 | € 2.897,27 | € 2,90 |
| week25 | 20.02.2017 00:00 | 27.02.2017 00:00 | € 305.020,56 | 95 | € 3.210,74 | € 3,21 |
| week26 | 27.02.2017 00:00 | 06.03.2017 00:00 | € 288.714,34 | 93 | € 3.104,46 | € 3,10 |
| week27 | 06.03.2017 00:00 | 13.03.2017 00:00 | € 279.420,96 | 93 | € 3.004,53 | € 3,00 |
| week28 | 13.03.2017 00:00 | 20.03.2017 00:00 | € 228.480,83 | 80 | € 2.856,01 | € 2,86 |
| week29 | 20.03.2017 00:00 | 27.03.2017 00:00 | € 172.768,48 | 65 | € 2.657,98 | € 2,66 |
| week30 | 27.03.2017 00:00 | 03.04.2017 00:00 | € 151.820,58 | 63 | € 2.409,85 | € 2,41 |
| week31 | 03.04.2017 00:00 | 10.04.2017 00:00 | € 123.179,15 | 56 | € 2.199,63 | € 2,20 |
| week32 | 10.04.2017 00:00 | 17.04.2017 00:00 | € 133.215,34 | 63 | € 2.114,53 | € 2,11 |
| week33 | 17.04.2017 00:00 | 24.04.2017 00:00 | € 181.813,46 | 84 | € 2.164,45 | € 2,16 |
| week34 | 24.04.2017 00:00 | 01.05.2017 00:00 | € 220.500,02 | 97 | € 2.273,20 | € 2,27 |
| week35 | 01.05.2017 00:00 | 08.05.2017 00:00 | € 195.636,88 | 82 | € 2.385,82 | € 2,39 |
| week36 | 08.05.2017 00:00 | 15.05.2017 00:00 | € 264.520,21 | 108 | € 2.449,26 | € 2,45 |
| week37 | 15.05.2017 00:00 | 22.05.2017 00:00 | € 187.978,44 | 77 | € 2.441,28 | € 2,44 |
| week38 | 22.05.2017 00:00 | 29.05.2017 00:00 | € 165.900,99 | 64 | € 2.592,20 | € 2,59 |
| week39 | 29.05.2017 00:00 | 05.06.2017 00:00 | € 223.074,92 | 86 | € 2.593,89 | € 2,59 |

## 8.3 Weekly results overview

Below, the results per week are displayed for the reliable, optimized and opportunistic strategy. The results shown here form the basis for the average results displayed in chapter 4.1. They are based on the default situation.

*Table 9: Weekly results in the optimized strategy*

Optimized

| | Bid size | IR-events | IR-up events | IR-down events | Reliability | Revenue | IR-fines | NA-fines | Total fines | Availability | Net revenue |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **week01** | 900 | 0 | 0 | 0 | 100.0% | €1,944 | €0 | €550 | €550 | 90.3% | €1,393 |
| **week02** | 2,400 | 0 | 0 | 0 | 100.0% | €5,256 | €0 | €1,234 | €1,234 | 90.1% | €4,021 |
| **week03** | 2,000 | 0 | 0 | 0 | 100.0% | €4,700 | €0 | €1,095 | €1,095 | 90.3% | €3,604 |
| **week04** | 2,700 | 0 | 0 | 0 | 100.0% | €6,588 | €0 | €697 | €697 | 90.7% | €5,890 |
| **week05** | 2,700 | 0 | 0 | 0 | 100.0% | €6,912 | €0 | €902 | €902 | 88.7% | €6,009 |
| **week06** | 3,800 | 0 | 0 | 0 | 100.0% | €9,120 | €0 | €596 | €596 | 89.8% | €8,523 |
| **week07** | 3,800 | 0 | 0 | 0 | 100.0% | €8,816 | €0 | €402 | €402 | 91.7% | €8,413 |
| **week08** | 3,800 | 0 | 0 | 0 | 100.0% | €9,006 | €0 | €647 | €647 | 89.6% | €8,358 |
| **week09** | 3,900 | 0 | 0 | 0 | 100.0% | €9,321 | €0 | €676 | €676 | 91.9% | €8,644 |
| **week10** | 3,900 | 0 | 0 | 0 | 100.0% | €9,594 | €0 | €529 | €529 | 89.6% | €9,064 |
| **week11** | 3,800 | 0 | 0 | 0 | 100.0% | €9,158 | €0 | €1,071 | €1,071 | 89.5% | €8,086 |
| **week20** | 3,900 | 0 | 0 | 0 | 100.0% | €11,310 | €0 | €579 | €579 | 92.0% | €10,730 |
| **week21** | 3,300 | 0 | 0 | 0 | 100.0% | €10,593 | €0 | €1,294 | €1,294 | 89.8% | €9,298 |
| **week22** | 3,500 | 0 | 0 | 0 | 100.0% | €10,850 | €0 | €1,474 | €1,474 | 89.4% | €9,375 |
| **week23** | 4,000 | 0 | 0 | 0 | 100.0% | €12,000 | €0 | €2,002 | €2,002 | 89.4% | €9,997 |
| **week24** | 3,400 | 0 | 0 | 0 | 100.0% | €9,724 | €0 | €1,291 | €1,291 | 90.0% | €8,432 |
| **week25** | 3,000 | 0 | 0 | 0 | 100.0% | €7,980 | €0 | €941 | €941 | 89.2% | €7,038 |
| **week26** | 1,700 | 0 | 0 | 0 | 100.0% | €4,097 | €0 | €910 | €910 | 90.2% | €3,186 |
| **week27** | 1,900 | 0 | 0 | 0 | 100.0% | €4,180 | €0 | €1,097 | €1,097 | 90.2% | €3,082 |
| **week28** | 3,000 | 0 | 0 | 0 | 100.0% | €6,330 | €0 | €936 | €936 | 89.9% | €5,393 |
| **week29** | 3,700 | 0 | 0 | 0 | 100.0% | €7,992 | €0 | €729 | €729 | 87.9% | €7,262 |
| **week30** | 3,200 | 1 | 0 | 1 | 100.0% | €7,264 | €661 | €1,212 | €1,874 | 90.5% | €5,389 |

*Table 10: weekly results in the opportunistic scenario*

Opportunistic

| | Bid size | IR-events | IR-up events | IR-down events | Reliability | Revenue | IR-fines | NA-fines | Total fines | Availability | Net revenue |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **week01** | 3,600 | 8 | 0 | 8 | 99.6% | €7,776 | €1,989 | €32,127 | €34,116 | 7.1% | €5,786 |
| **week02** | 8,000 | 9 | 0 | 9 | 99.6% | €17,520 | €3,093 | €92,291 | €95,384 | 0.0% | €14,426 |
| **week03** | 8,800 | 8 | 0 | 8 | 99.6% | €20,680 | €5,553 | €129,574 | €135,127 | 0.0% | €15,126 |
| **week04** | 12,000 | 7 | 4 | 3 | 99.7% | €29,280 | €3,821 | €198,600 | €202,422 | 0.0% | €25,458 |
| **week05** | 11,400 | 8 | 1 | 7 | 99.6% | €29,184 | €5,580 | €194,572 | €200,152 | 0.0% | €23,603 |
| **week06** | 14,300 | 8 | 3 | 5 | 99.6% | €34,320 | €3,802 | €237,623 | €241,426 | 0.0% | €30,517 |
| **week07** | 12,200 | 8 | 5 | 3 | 99.6% | €28,304 | €1,002 | €181,298 | €182,301 | 0.0% | €27,301 |
| **week08** | 13,500 | 7 | 2 | 5 | 99.7% | €31,995 | €2,333 | €215,143 | €217,477 | 0.0% | €29,661 |
| **week09** | 13,700 | 7 | 4 | 3 | 99.7% | €32,743 | €4,422 | €221,574 | €225,996 | 0.0% | €28,320 |
| **week10** | 14,100 | 7 | 3 | 4 | 99.7% | €34,686 | €5,139 | €238,492 | €243,631 | 0.0% | €29,546 |
| **week11** | 11,900 | 7 | 3 | 4 | 99.7% | €28,679 | €4,766 | €181,515 | €186,281 | 0.0% | €23,912 |
| **week20** | 14,400 | 7 | 7 | 0 | 99.7% | €41,760 | €3,048 | €288,753 | €291,802 | 0.0% | €38,711 |
| **week21** | 13,400 | 7 | 2 | 5 | 99.7% | €43,014 | €7,897 | €294,933 | €302,830 | 0.0% | €35,116 |
| **week22** | 14,100 | 7 | 4 | 3 | 99.7% | €43,710 | €5,421 | €307,240 | €312,661 | 0.0% | €38,288 |
| **week23** | 11,300 | 7 | 3 | 4 | 99.7% | €33,900 | €9,661 | €206,287 | €215,949 | 0.0% | €24,238 |
| **week24** | 10,300 | 8 | 2 | 6 | 99.6% | €29,458 | €4,034 | €176,421 | €180,456 | 0.0% | €25,423 |
| **week25** | 12,200 | 7 | 0 | 7 | 99.7% | €32,452 | €8,610 | €219,494 | €228,105 | 0.0% | €23,841 |
| **week26** | 8,000 | 8 | 0 | 8 | 99.6% | €19,280 | €5,610 | €114,988 | €120,598 | 0.0% | €13,669 |
| **week27** | 7,300 | 8 | 0 | 8 | 99.6% | €16,060 | €3,837 | €90,862 | €94,699 | 0.0% | €12,222 |
| **week28** | 13,800 | 7 | 1 | 6 | 99.7% | €29,118 | €5,388 | €209,758 | €215,147 | 0.0% | €23,729 |
| **week29** | 13,100 | 8 | 3 | 5 | 99.6% | €28,296 | €4,478 | €189,947 | €194,425 | 0.0% | €23,817 |
| **week30** | 14,500 | 7 | 2 | 5 | 99.7% | €32,915 | €8,006 | €236,207 | €244,214 | 0.0% | €24,908 |

*Table 11: weekly results in the reliable scenario*

Reliable

| | Bid size | IR-events | IR-up events | IR-down events | Reliability | Revenue | IR-fines | NA-fines | Total fines | Availability | Net revenue |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **week01** | 300 | 0 | 0 | 0 | 100.0% | €648 | €0 | €0 | €0 | 100.0% | €648 |
| **week02** | 1,000 | 0 | 0 | 0 | 100.0% | €2,190 | €0 | €0 | €0 | 100.0% | €2,190 |
| **week03** | 1,000 | 0 | 0 | 0 | 100.0% | €2,350 | €0 | €0 | €0 | 100.0% | €2,350 |
| **week04** | 1,700 | 0 | 0 | 0 | 100.0% | €4,148 | €0 | €0 | €0 | 100.0% | €4,148 |
| **week05** | 1,500 | 0 | 0 | 0 | 100.0% | €3,840 | €0 | €0 | €0 | 100.0% | €3,840 |
| **week06** | 2,900 | 0 | 0 | 0 | 100.0% | €6,960 | €0 | €0 | €0 | 100.0% | €6,960 |
| **week07** | 3,100 | 0 | 0 | 0 | 100.0% | €7,191 | €0 | €0 | €0 | 100.0% | €7,191 |
| **week08** | 2,900 | 0 | 0 | 0 | 100.0% | €6,873 | €0 | €0 | €0 | 100.0% | €6,873 |
| **week09** | 3,000 | 0 | 0 | 0 | 100.0% | €7,170 | €0 | €0 | €0 | 100.0% | €7,170 |
| **week10** | 2,900 | 0 | 0 | 0 | 100.0% | €7,134 | €0 | €0 | €0 | 100.0% | €7,134 |
| **week11** | 2,400 | 0 | 0 | 0 | 100.0% | €5,784 | €0 | €0 | €0 | 100.0% | €5,784 |
| **week20** | 2,800 | 0 | 0 | 0 | 100.0% | €8,120 | €0 | €0 | €0 | 100.0% | €8,120 |
| **week21** | 1,600 | 0 | 0 | 0 | 100.0% | €5,136 | €0 | €0 | €0 | 100.0% | €5,136 |
| **week22** | 1,400 | 0 | 0 | 0 | 100.0% | €4,340 | €0 | €0 | €0 | 100.0% | €4,340 |
| **week23** | 1,100 | 0 | 0 | 0 | 100.0% | €3,300 | €0 | €0 | €0 | 100.0% | €3,300 |
| **week24** | 1,300 | 0 | 0 | 0 | 100.0% | €3,718 | €0 | €0 | €0 | 100.0% | €3,718 |
| **week25** | 2,000 | 0 | 0 | 0 | 100.0% | €5,320 | €0 | €0 | €0 | 100.0% | €5,320 |
| **week26** | 400 | 0 | 0 | 0 | 100.0% | €964 | €0 | €0 | €0 | 100.0% | €964 |
| **week27** | 800 | 0 | 0 | 0 | 100.0% | €1,760 | €0 | €0 | €0 | 100.0% | €1,760 |
| **week28** | 1,400 | 0 | 0 | 0 | 100.0% | €2,954 | €0 | €0 | €0 | 100.0% | €2,954 |
| **week29** | 2,300 | 0 | 0 | 0 | 100.0% | €4,968 | €0 | €0 | €0 | 100.0% | €4,968 |
| **week30** | 100 | 0 | 0 | 0 | 100.0% | €227 | €0 | €0 | €0 | 100.0% | €227 |

## 8.4 Sensitivity analysis

### 8.4.1 FCR price

*Table 12: Net revenue for three strategies for different FCR prices*

| | Reliable net revenue | Optimized net revenue | Opportunistic net revenue |
|---|---|---|---|
| **1** | €1,722 | €2,713 | €9,690 |
| **2** | €3,445 | €5,427 | €19,380 |
| **3** | €5,168 | €8,141 | €29,070 |
| **4** | €6,890 | €10,855 | €38,760 |

*Table13: Bid sizes for three strategies for different FCR prices*

| | Reliable bid size | Optimized bid size | Opportunistic bid size |
|---|---|---|---|
| **1** | 1,722 | 3,104 | 11,631 |
| **2** | 1,722 | 3,104 | 11,631 |
| **3** | 1,722 | 3,104 | 11,631 |
| **4** | 1,722 | 3,104 | 11,631 |

### 8.4.2 FAD

*Table 14: Net revenue for three strategies for different values of FAD*

| | Reliable net revenue | Optimized net revenue | Opportunistic net revenue |
|---|---|---|---|
| **0.05** | €4,322 | €6,711 | €9,203 |
| **0.10** | €4,322 | €6,875 | €11,034 |
| **0.20** | €4,322 | €6,872 | €24,437 |
| **0.30** | €4,322 | €6,902 | €29,609 |
| **0.50** | €4,322 | €6,902 | €49,356 |

*Table 15: Bid size for three strategies for different values of FAD*

| | Reliable bid size | Optimized bid size | Opportunistic bid size |
|---|---|---|---|
| **0.05** | 1,722 | 2,968 | 3,872 |
| **0.10** | 1,722 | 3,077 | 4,727 |
| **0.20** | 1,722 | 3,104 | 11,631 |
| **0.30** | 1,722 | 3,104 | 13,063 |
| **0.50** | 1,722 | 3,104 | 21,772 |

### 8.4.3 NA-fine regime

*Table 16: Net revenue for three strategies for different values of NA-fine regime*

| | Reliable net revenue | Optimized net revenue | Opportunistic net revenue |
|---|---|---|---|
| **0.01** | €4,322 | €24,244 | €24,437 |
| **0.10** | €4,322 | €22,541 | €24,437 |
| **0.50** | €4,322 | €15,631 | €24,437 |
| **1.00** | €4,322 | €9,781 | €24,437 |
| **5.00** | €4,322 | €7,567 | €24,437 |
| **10.00** | €4,322 | €6,872 | €24,437 |
| **15.00** | €4,322 | €6,497 | €24,437 |
| **20.00** | €4,322 | €6,230 | €24,437 |
| **50.00** | €4,322 | €5,451 | €24,437 |

*Table 17: Bid size for three strategies for different NA-fine regime values*

| | Reliable bid size | Optimized bid size | Opportunistic bid size |
|---|---|---|---|
| **0.01** | 1,722 | 11,622 | 11,631 |
| **0.10** | 1,722 | 11,318 | 11,631 |
| **0.50** | 1,722 | 10,031 | 11,631 |
| **1.00** | 1,722 | 5,190 | 11,631 |
| **5.00** | 1,722 | 3,427 | 11,631 |
| **10.00** | 1,722 | 3,104 | 11,631 |
| **15.00** | 1,722 | 2,940 | 11,631 |
| **20.00** | 1,722 | 2,818 | 11,631 |
| **50.00** | 1,722 | 2,463 | 11,631 |

### 8.4.4 IR-fine regime

*Table 18: Net revenue for three different strategies for different values of IR-fine regime*

| | Reliable net revenue | Optimized net revenue | Opportunistic net revenue |
|---|---|---|---|
| **0.1** | €4,322 | €6,899 | €40,785 |
| **0.5** | €4,322 | €6,887 | €28,109 |
| **1.0** | €4,322 | €6,872 | €24,437 |
| **2.0** | €4,322 | €6,843 | €21,301 |
| **5.0** | €4,322 | €6,765 | €18,265 |

*Table 19: Bid sizes for three different strategies for different values of IR-fine regime*

| | Reliable bid size | Optimized bid size | Opportunistic bid size |
|---|---|---|---|
| **0.1** | 1,722 | 3,104 | 20,554 |
| **0.5** | 1,722 | 3,104 | 13,577 |
| **1.0** | 1,722 | 3,104 | 11,631 |
| **2.0** | 1,722 | 3,100 | 10,031 |
| **5.0** | 1,722 | 3,081 | 7,927 |